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# Advanced Driver Assistance Based on Front-View and Rear-Side-View Scene Analysis

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**Abstract.** This paper proposes a high-performance advanced driver assistance system that analyses front-view driving scenes and rear-side-view scenes. Dense optical flow analysis is calculated for both views to extract motion information. The system performs ego-lane position identification via an effective fuzzy system and indicates if the vehicle is driving on an inner or outer lane. Extracted flow intensities are utilized as the input for deep convolutional neural networks to issue warning events. The front-view event warning system is more responsive to various types of potential approaching dangers because there is no need to detect vehicles first. The rear-side-view scene analysis provides safety check for vehicle doors. Optical flow information and neural networks are also used for rear-side-view scene analysis. The experimental results have shown that the proposed methods can effective detect events or dangerous conditions and help increase the safety of the drivers and road users.

## 1. Introduction

With the development of the technology, Advanced Driver Assistance Systems (ADAS) has great breakthroughs in recent years. More than a decade ago, ADAS was limited by technical limitations and the cost of hardware and equipment, so its penetration rate was still not high enough. However, in the recent five years, many vehicles are equipped with ADAS to reduce car accidents. The researches on ADAS are also increasing, including forward collision warning systems, lane departure warning systems, overtaking assistance systems [1], and blind zone alert systems [2]. Most ADAS systems use traditional sensors for event detection. But for lower cost systems, methods to achieve driver assistance with camera vision have also become popular [3], [4].

In this work, we propose to analyze both front-view and rear-side-view scenes for driver assistance. For front-view scenes, the goal is to accurately detect event and issue warnings without having to identify or classify vehicles first. The motivation of the proposed event detection scheme is to simulate human instinct. Human would intuitively dodge first before recognizing a fast-approaching object when sensing the approaching movement. Therefore, when abnormal motion patterns are detected, the proposed system would generate warning events without performing vehicle or object detection. The alerting events include cut-in vehicles in front of the current lane, high-speed overtaking vehicles in the neighbouring left or right lanes, accidents in current or neighboring lanes, and other rare events such as falling objects or obstacles. However, the proposed system does not further classify the events into different categories. For rear-side-view scene analysis, a vehicle door safety system is implemented.

The system prevents drivers from opening the vehicle door recklessly when there are other vehicles approaching from the rear side.

Optical flow is a popular way to estimate motion in ADASs. Research works have investigated both regulation and polar representation of optical flow for ADAS applications [5]. There are also solutions to deal with large displacements and poorly textured regions when applying optical flow algorithms [6]. In the proposed system, optical flow information is chosen for motion feature extraction because the above mentioned research works have performed empirical study to validate its accuracy and shown that it is applicable for various driving scenarios.

## 2. Front-view Scene Analysis for Driver Assistance

For front-view scene analysis, lane detection is performed based on the perspective analysis and filtering method proposed in [7]. The vanishing point can be determined after the lane detection procedure. Then, the Farneback algorithm [8] is used to compute the dense optical flow since it is computationally efficient and results in accurate flow vectors. The optical flow vectors are normalized according to the size of the scene and a low pass filter is applied to suppress noises. The proposed ego-lane position identification procedure using fuzzy system is elaborated in sub-section 2.1. The front view event warning system is described in sub-section 2.2.

### *2.1. Ego-lane Position Identification*

As shown in Figure 1, the purpose of the ego-lane position identification scheme is to distinguish if the areas beside the current lane belong to the road boundary or a neighbouring lane. Based on the lane detection method proposed in [7], the vanishing line is determined to separate the lane area and sky area.

(a) (b) (c)

**Figure 1.** Ego-Lane Position Identification: (a) Inner Lane; (b) Middle Lane; (c) Outer Lane

According to the positions of the vanishing line and the base line, the system sets up a left region Rl and right region Rr for feature extraction, as shown in Figure 2 (a). Then, the optical flow densities $d_l$ and $d_r$ are calculated in the regions Rl and Rr, respectively. Eq. (1) is used to calculate the optical flow density $d_l$ in region Rl. In Eq. (1), $r(x,y)$ denotes the magnitude of the flow vector at position $(x,y)$. Density $d_r$ is defined similarly for region Rr.

$$d_l = \frac{\sum_{(x,y)\in Rl} r(x,y)}{Area(Rl)} \tag{1}$$

When we observe the optical flow vectors in the front-view videos, we can see that the flow densities exhibit some particular patterns. When a vehicle is driving close to a road boundary, the road boundary would generate dense and strong flow vectors, as shown in Rr of Figure 2 (a) and Rl of Figure 2 (b). On the contrary, the flow densities in the neighbouring lanes are relatively weaker and sparser as shown in Rl of Figure 2 (a), Rr of Figure 2 (b), and both Rl and Rr in Figure 2 (c). As a result, if a vehicle is driving in the inner or outer lane which is closer to a road boundary, the difference between flow densities in Rl and Rr would be larger. If the vehicle is driving in the middle lane, the difference between flow densities in Rl and Rr would be smaller. Based on the above mentioned observations, the difference between the optical flow densities $d_l$ and $d_r$ is calculated as described in Eq. (2).

$$diff = d_l - d_r \tag{2}$$

The characteristics of fuzzy logic are being flexible and tolerant to imprecise data. Therefore, a fuzzy system is designed for ego-lane position identification to incorporate expert experiences. Based on the knowledge of flow densities, nine types of membership are defined in the proposed system. A reference value is applied to evaluate the membership. The parameters L, M, S, and DL are the reference values in the grade of membership. Each membership function outputs a membership grade which ranges from 0 to 1. For membership values that are smaller than one, Gaussian membership functions are used.

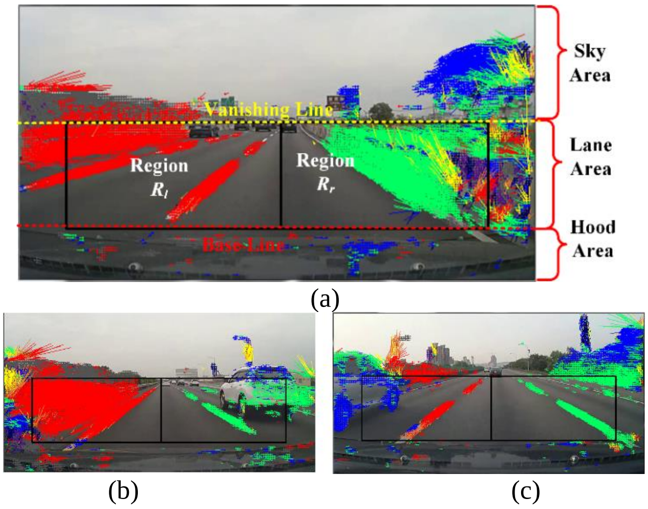


**Figure 2**. Regions for Left and Right Density Computation

A simplified Takagi-Sugeno-Kang (TSK) fuzzy system is used in the proposed system. The firing strength are used as the weights of a function in a TSK fuzzy system. The firing strength $w_i$ is obtained using minimum composition. There are 9 fuzzy rules in the proposed method. The output $z$ is defined in the following equation.

$$z = \frac{\sum_{i=1}^{9} w_i f_i}{\sum_{i=1}^{9} w_i} \tag{3}$$

The corresponding examples for different outputs representing the lane status are displayed in Figure 1 (a), (b), and (c).

*2.2. Front-view Event Detection*

Based on the ego-lane position identification results described in the previous sub-section, an event warning system is developed. The events to be detected are cut-in vehicles in front of the current lane, high-speed overtaking vehicles in neighbouring lanes, accidents in current or neighbouring lanes, and other rare events such as obstacles or falling objects. The lane condition is checked first. If the left or right area does not belong to a neighbouring lane, there will be no event associated with it. For left, centre, or right lane regions, a classifier based on an inception-v4 network is used to detect front-view events. Note that the events are not further classified. The convolutional neural network only outputs binary output for event detection. The reason of optical flow intensities as input is that we assume that when an event occurs, it would generate flow vectors with specific orientations. And the flow vectors of events are quite different from those of normal conditions without any events. The network would learn the patterns of these flow vectors from the training data.

## 3. Rear-Side-View Scene Analysis for Vehicle Door Safety Check

The purpose of rear-side-view scene analysis is to prevent the dangerous conditions while opening the vehicle doors. If vehicle drivers do not pay attention to the motorcycles or bicycles and open the vehicle door recklessly, the action is very likely to cause collision accidents. According to statistics, accidents caused by opening vehicle doors occupy a very large portion of all vehicle accidents. Therefore, preventing collision accident caused by opening vehicle doors is very important.

The system automatically detects the car door position, and defines region of interest (ROI), which is an area we can detect the approaching vehicles from the rear-side view. We use the probability density function of Gaussian models to automatically detect the position of the colours of the ego-vehicle in the

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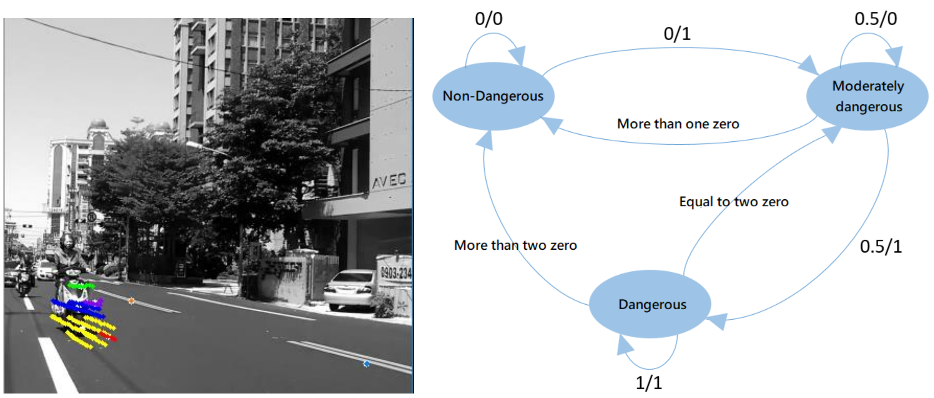
image. Since all the system need is the part of the image which includes the neighbouring lane, we remove the part of ego-vehicle detected by the Gaussian models and retain the area of ROI only. In rear-side-view scene, Farneback optical flow is also used to detect moving objects. We calculate one optical flow point for every 15 pixels in the entire ROI. After obtaining the optical flow information, the flow vectors are clustered to acquire trajectory groups for feature extraction.

### *3.1. Trajectory clustering and feature extraction*
We use Spectral Clustering algorithm [9] to group the trajectories of each image. As shown in Figure 3 (a), all the tracks in the picture are clustered into several groups, different colours in the picture represent different groups. After grouping, we extract the features of the trajectory clusters as the feature vector to be trained later. The system takes 25 trajectories with the highest average flow intensity for feature extraction. The extracted features are maximum intensity, average intensity, average angle, standard deviation of angle, group average coordinate position, and the distance from the group average coordinate to the bottom left of each group.




(a) (b)

**Figure 3.** Trajectory Clustering and State Transition Model.

### *3.2. Vehicle Door Safety Check*
The extracted features of the trajectory clusters described in the previous sub-section are used as input of an artificial neural network to predict dangerous conditions. The prediction result is whether each frame belongs to a dangerous state or a non-dangerous state. The dangerous state is expressed as 1, and a none dangerous state is expressed as 0. Therefore, this result is a long list of 0 or 1 components and can be considered as a series of sequences.

Suppose in the sequence, we retrieve a small sequence as 00000101111100000. In the sequence, we can see that after encountering the first dangerous state 1, we encounter a non-dangerous sate 0, and then the next state is 1 again. In this case, it is probable that the 0 between two 1's is a noise. The states should not switch frequently from dangerous and non-dangerous states within tenths of a second. Therefore, we use a finite state transition mechanism to remove noises and ensure that the predicted result is more robust. Figure 3 (b) is the design of the state transition. Through the state transition model, we can get the corrected prediction results.

## 4. Experimental Results
For front-view scene analysis, the dataset used for experiments includes videos recorded using two different event recorders, PAPAGO P1 and Mio MiVue™ 588. The duration of the experimental videos is 145 minutes in total. The events in the videos include high-speed overtaking vehicles in left and right neighbouring lanes, cutting-in vehicles with insufficient distance in the current lane, and vehicles with abnormal motion patterns. In addition, we downloaded 8 different videos with accidents from the YouTube to test the ability of accident event detection. The duration of the downloaded accident videos is 356 seconds in total. Each video has an accident in it. For rear-side-view scene analysis, experimental

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videos are recorded using three different vehicles parked at the road-sides on different roads. The duration of the videos are 50 minutes in total. Four-fold cross validation is used in the experiments.

We compare the proposed ego-lane position identification scheme with different methods in Figure 4. The baseline method is to perform thresholding directly on the extracted features of optical flow densities. Using thresholding directly could not result in satisfying accuracy although the difference of optical flow densities includes inherit information to identify ego-lane position. We also use the flow density features and apply classical Artificial Neural Network (ANN) and Support Vector Machine (SVM) classifier for comparison. The classification accuracy increases compared with the baseline thresholding method. However, the results can still be improved. The proposed fuzzy system can achieve higher accuracy because fuzzy logic can build the classifier that can deal with high complexity based on expert experiences and human observations while retaining flexibility and tolerance of imprecise data. To compare with other methods, we consider the works in [7] and [10]. In [7] and [10], the authors did not provide inner and outer lane classification explicitly. However, we try to use the information provided in their systems to retrieve the ego-lane position status. In [7], the geometry of adjacent lanes is inferred using their multiple lane estimation. In [10], the presence of adjacent lanes is inferred using their tracked vehicle lane assignments. We can observe that the proposed method exhibits higher accuracy compared to these methods, as shown in Figure 4.

We compare the proposed event detection system with [10] and [11] in Figure 5. In [10], the vehicles need to be detected before the events can be specified. However, there are some occasions when vehicles would have abnormal appearances in the accident scenes. In such circumstances, the vehicles cannot be detected and therefore the events cannot be recognized effectively. Also, partial vehicles that have not entered completely into the scene cannot be detected effectively, either. The proposed method exhibits much higher recall rates in left, centre, and right lanes compared with [10] due to the above mentioned reasons. However, the method in [10] has slightly higher precision rates in left and right lanes, which means that their method has fewer false alarms. The reason is that all the recognized events are based on detected vehicles in [10]. However, the overall F-measure of the proposed method is higher than that of [10] in all three lanes. For the method in [11], only overtaking vehicle events in the neighbouring lanes are considered. Therefore, no event detection statistics are shown for the centre lane. Also, the method in [11] does not recognize accident events. Both the precision and recall rates of the proposed method are higher than those of [11]. For the precision rate, the proposed ego-lane position identification makes the subsequent event detection module more confident on the detection results of the neighbouring lanes. For the recall rate, the method in [11] does not recognize accident events and therefore these events would result in increasing number of misses in their system.

Figure 6 plots the dangerous condition detection accuracy based on rear-side-view scenes. For better vehicle door safety protection, a high recall rate is required. The requirement of the precision rate can be less strict. We can observe that if there is no trajectory clustering and the flow vectors are directly as input of the neural networks, the accuracy is lower. Performing trajectory grouping for feature extraction can significantly increase the detection accuracy.

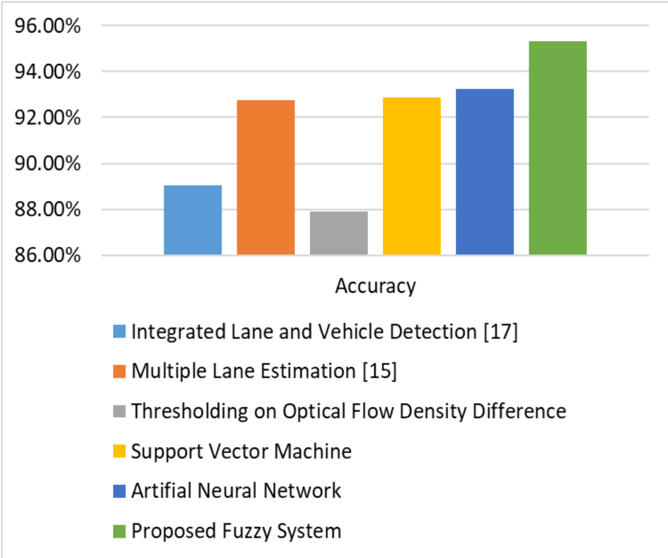


**Figure 4.** Ego-Lane Position Identification Using Different Methods

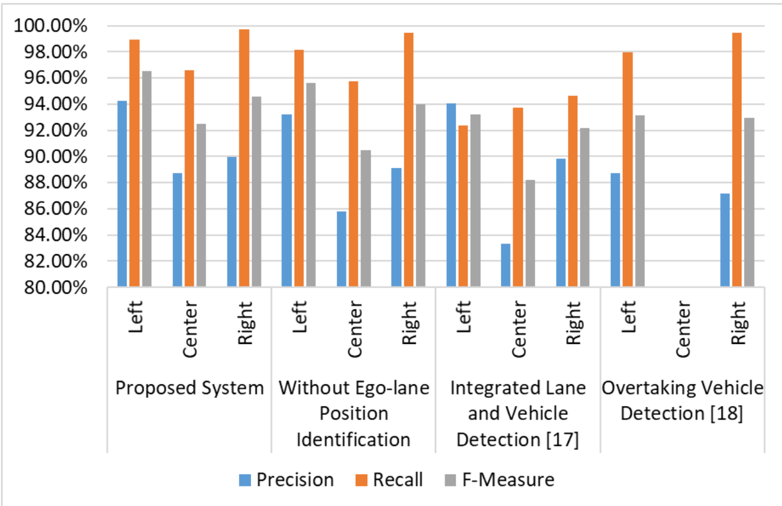


**Figure 5.** Front-View Event Detection Accuracy Using Different Methods

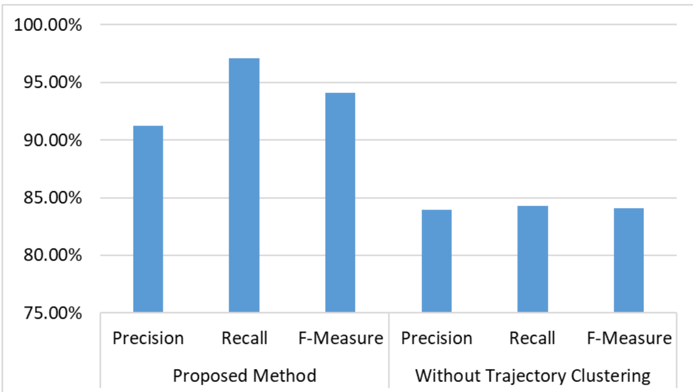


**Figure 6.** Rear-Side-View Dangerous Condition Detection Accuracy

## 5. Conclusions

In this work, a system that analyses front-view and rear-side-view scenes is developed to assist drivers. The proposed schemes can achieve real-time performance. For front view scenes, it utilizes dense optical flows and a fuzzy system to perform ego-lane position identification automatically. The ego-lane position information provides important information for the subsequent event warning applications. For event detection, the proposed system imitates human instinct to detect potential dangers without detecting and recognizing vehicles first. Optical flow vectors are used for feature extraction and a convolutional neural network is utilized. Since the proposed event detection is not based on vehicle appearances, the system does not have to consider various types of vehicle appearances in the training data. The events could be detected when the optical flow vectors are different from the normal flow patterns. The variety of events detected by the proposed method is larger compared to existing methods based on vehicle detection and tracking. The proposed method has a much higher detection recall rate, and the overall F-measure is also higher. For rear-side-view scene analysis, we also use optical flows as features to analyse the image to detect dangerous events behind the vehicle. Our system achieves the automatic detecting the ROI using the colour of the ego-vehicle. By extracting the features of trajectory clusters, the accuracy of detection is enhanced. The experiment results verify that the proposed system has satisfying reliability.

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