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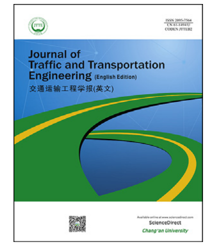

Review Article

Lane departure warning systems and lane line detection methods based on image processing and semantic segmentation: A review

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HIGHLIGHTS

- Lane departure warning systems in road traffic.
- Lane line detection algorithms based on Image processing and analysis.
- Semantic segmentation methods for lane line identification.
- Machine learning, deep learning and neural network.
- New methods of 3D lane line detection.

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ABSTRACT

Recently, the development and application of lane line departure warning systems have been in the market. For any of the systems, the key part of lane line tracking, lane line identification, or lane line departure warning is whether it can accurately and quickly detect lane lines. Since 1990s, they have been studied and implemented for the situations defined by the good viewing conditions and the clear lane markings on road. After then, the accuracy for particular situations, the robustness for a wide range of scenarios, time efficiency and integration into higher-order tasks define visual lane line detection and tracking as a continuing research subject. At present, these kinds of lane marking line detection methods based on machine vision and image processing can be divided into two categories: the traditional image processing and semantic segmentation (includes deep learning) methods. The former mainly involves feature-based and model-based steps, and which can be classified into similarity- and discontinuity-based ones; and the model-based step includes different parametric straight line, curve or pattern models. The semantic segmentation includes different machine learning, neural network and deep learning methods, which is the new trend for the research and application of lane line departure warning systems. This paper describes and analyzes the lane line departure warning

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systems, image processing algorithms and semantic segmentation methods for lane line detection.

1. Introduction

With the rapid development of the global automobile industry, it has become one of the largest industries in the world, and the problem of road or lane perception is a crucial enabler for advanced driver assistance systems (Hillel et al., 2014; Liang et al., 2020). At present, it has become the main industry in the national economic development of Germany, Japan, South Korea, United States and other countries. The automobile industry has a strong role in promoting and leading the upgrading of industrial structure and the development of other related industries in each developed country. At the same time, many countries also appear with the contradiction between the rapid growth of automobile sales and the lack of basic road construction. Some adverse phenomena such as automobile traffic accidents, energy waste, road congestion and environmental pollution have become more and more frequent and serious in many countries (Yu, 2017). According to the statistics, there are about 1.3 million people died in traffic accidents every year in the world (Sun et al., 2018). The frequent traffic accidents and the resulting casualties have made a huge burden for the development of the society (Sivaraman and Trivedi, 2013). In order to solve this kind of problems affecting public health and life, the United Nations held a general assembly in March 2010 and adopted resolution A/RES/64/255. In the resolution, 2011–2020 is defined as the 10-year road traffic safety action (Sun et al., 2018). It proposed that countries around the world should take active actions to reduce the frequency of road traffic accidents and the probability of death. Meanwhile, the resolution also pointed out that 90% of the world's road traffic accidents occurred in some low-income countries even the number of vehicles owned by these low-income countries is much lower than the total number of the world. Hence the traffic safety of these low-income countries needs to be solved and improved urgently (WHO, 2019).

In the statistics of the Ministry of Transport in China, about 50% of the automobile traffic accidents are caused by the vehicles deviating from the normal driving lane. The main reason is that drivers are distracted or tired. 23% of the drivers fell asleep on the steering wheel at least once a month; 66% of the truck drivers dozed off during driving; 28% of the truck drivers fell asleep on the steering wheel within one month. Such an alarming proportion is enough to prove the importance of preventing lane departure. According to the estimation by the Federal Highway Administration in United States, 44% of all fatal traffic accidents in the United States in 2002 were related to lane departure, which is also regarded as the main cause of vehicle rollover accidents. One out of four drivers has experienced injuries and deaths caused by lane departure. Hence, as computer technology development, the application of lane departure warning system (LDWS) and automatic driving technology is an important innovative technology to improve road safety, which can effectively reduce the occurrence of traffic accidents, decrease the loss of life by more than 50%. This is a new application technology that integrates various technical means such as artificial intelligence, intelligent network, sensor perception network, computer vision, etc. (Gaikwad and Lokhande, 2015; Hillel et al., 2014).

Since then, with the continuous advancement of enterprises and related researches for LDWS, more and more application solutions are gradually being applied in various driving scenarios (Bartolini, 2015; Sternlund, 2017). The vehicle deviation warning system mainly includes three modes for data acquisition based on optical camera, lidar and infrared sensors (Narote et al., 2018; Yenikaya et al., 2013), or the combination of the sensors (Aessandretti et al., 2007; Liang et al., 2020). Due to the high cost and technical difficulty of the latter, the current applications of lidar and infrared sensors are few. The LDWS based on machine vision and image processing is the focus of current applications and researches. The system mainly collects and quantitatively analyzes road information based on visual sensors, extracts lane lines under the road environment, and completes the part of the assisted driving function under comprehensive road conditions, such as lane line detection, lane keeping, preceding vehicle following, etc. (Gopalan et al., 2012). To a certain extent, it can alleviate driver fatigue, reduce the probability of traffic accidents, and improve road traffic safety.

With the in-depth study of the vehicle deviation warning system, the assisted driving function is constantly being improved and developed. Among them, the correct detection of the lane lines in the road scene has an important impact on the applications, with various functions in the assisted driving system (Du and Tan, 2016; Liang et al., 2020; Shin et al., 2014). However, in some scenes, there are also some situations where the detection accuracy of the lane lines is insufficient, and the lane line in the road scene cannot be quickly and accurately extracted, which hinders the popularization and application of the assisted driving system in the current automotive market.

The lane line detection belongs to linear object detection/extraction, and this technology has a wide range of applications (Yenikaya et al., 2013; Yi et al., 2015). The lane line detection in an assisted driving system is similar to the road detection in an aerial or a remote-sensing image by image processing and deep learning methods (Wang et al., 2017; Yuan et al., 2015), or the crack detection in a pavement image (Wang et al., 2019, 2020a, 2020b). Therefore, a lot of algorithms/methods in road detection and crack extraction can also be used for reference to the lane line detection. Even though a number of the vehicle deviation warning systems appear in market today, the lane line detection accuracy and speed still cannot meet the road traffic requirements. At present, there are two kinds of lane line detection methods: lane line detection based on machine vision/image processing and lane line detection based on semantic segmentation. The method based on image processing has a strong advantage in the real-time and stability of the system, but it has poor adaptability to the scene and cannot meet the applications of complicated and multiple scenes. The detection method based on the semantic segmentation trains the model through a large number of datasets, which makes the model obtain strong feature extraction ability, and has the stronger adaptability and robustness as a whole; with the continuous iteration of the model, however, the whole network model becomes more and more complex, and also needs strong computing ability to support.

This paper attempts to describe and sum up the lane line detection algorithms/methods through the comparative analysis, which may be useful for the researchers to further improve the accuracy and speed of lane line detection in urban road and highway scenes, so that it can be more effectively applied to various driving scenes. A literature review is provided in lane departure warning systems and lane line detection methods based on image processing and semantic segmentation. Over the past two decades, the vision-based lane line detection has progressed from its infancy into maturity. This paper describes and discusses LDWS in four aspects. (1) Lane departure warning systems in Section 2: in the intelligent assistant driving system, there is a subsystem which has been paid more and more attention, that is LDWS. (2) Status of lane line detection based on image processing and computer vision in Section 3: although the traditional algorithms/methods have been gradually replaced by the semantic segmentation methods such as deep learning method in recent years, many of the traditional method/algorithm design ideas and details are still worthy of reference and learning. (3) Status of the lane line detection based on semantic segmentation network: semantic segmentation network is a model based on neural network and deep convolution network, etc., whose most basic task is to classify different kinds of points in the image, and aggregate the same kind of points, so as to distinguish different target objects in the image. (4) Conclusions: anyhow, from the existing technical level, the most important factors affecting the reliability of the vision-based LDWS are algorithms for lane line detection; hence, there are still a lot of researches need to continue for LDWS.

2. Lane departure warning systems

Since 1980s, some developed countries, represented by Germany, Japan and the United States, have adopted advanced information and communication technology, electronic sensing technology, automatic control technology, artificial intelligence technology and systems technology in solving the similar traffic problems (such as road congestion, energy waste, traffic accidents, environmental pollution, etc.) faced by countries around the world. In order to gradually establish a comprehensive, real-time, accurate and efficient transportation management system, LDWS integrates the technologies, and carries out practice and application in surface road traffic and management (Zhou, 2016). Since 1994, the term intelligent transportation system (ITS) has been widely recognized all over the world. ITS effectively integrates various advanced sciences and technologies (electronic control technology, data communication technology, computer technology, automatic control theory, sensor technology, information technology, artificial intelligence, etc.) and applies them to road transportation, vehicle manufacturing and service control. Its application effectively enhances the communication and phase between vehicles, roads and users. Therefore, it can effectively reduce road traffic accidents, reduce vehicle transportation costs, alleviate road traffic congestion, decrease vehicle environmental pollution, improve the overall transportation efficiency and ensure the safety of road traffic, thus improving the overall social and economic benefits (Li, 2018).

With the continuous development and application of intelligent transportation system, safety driving assistant system (SDAS) has gradually come into people's sight, and gradually popularized in people's life. In the normal driving process of the vehicle, if facing sudden accidents, the intelligent auxiliary driving system can immediately provide some services such as emergency braking, auxiliary driving decision or emergency warning, so as to maximize the stability and safety of vehicle driving and minimize the economic losses and casualties caused by traffic accidents. In the intelligent assistant driving system, there is a subsystem which has been paid more and more attention, that is lane departure warning system (LDWS) (Chen and Boukerche, 2020; Liang, 2017).

LDWS is an important module of SDAS. It is a kind of safety system that can give early warning to the driver when the vehicle is about to or has already deviated from the lane. LDWS itself cannot control the driving vehicles actively to prevent the lane departure events that may happen soon. As shown in Fig. 1, the core purpose of LDWS is to warn drivers to reduce or avoid lane departure events. LDWS obtains the road information near the driving vehicle through the relevant sensors, and then analyzes the state of the driving vehicle, the warning threshold and warning time set in the system, and calculates whether the vehicle has the trend of deviating from the current driving lane. When the steering light of the driving vehicle is not turned on, and the driving vehicle is about to deviate or has already deviated, LDWS will send out a warning signal to the driver through hearing, tactile or visual means (Liang, 2017). LDWS generally includes lane line detection, lane line fitting, departure decision and warning release. LDWS has its own features as follows.

(1) It supports lane keeping while driving. A camera is used to identify the lane markings.

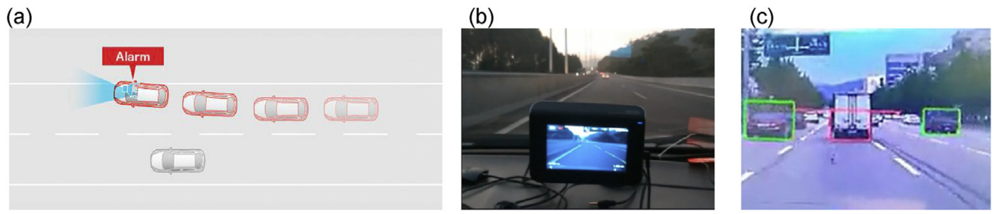

Fig. 1 – Demonstration of diagram of lane departure warning system and real system. (a) Diagram of lane departure warning (Lu et al., 2010). (b) Monitor in a car. (c) Warning based on front vehicle.

(2) If the vehicle approaches the identified marking line and is likely to leave the driving lane, it will be brought to the attention of the driver through the vibration of the steering wheel.
(3) If it identifies lane lines on both sides, then it is on standby. This is shown by a green indicator in the instrument cluster.
(4) When it is on standby, if the turn signal is turned on before crossing the marking line, there will be no warning, because it will accept a purposeful lane change.
(5) Since it is designed for driving on expressways and rural roads with good conditions, it usually starts to work when the speed is higher than 65 km/h.

As the above characteristics of LDWS, this research area still has a lot to do.

On normal highways or the highways with high degree of structure, the state of vehicles can be basically divided into four situations, as shown in Fig. 2. The first is unconscious lane departure. In this case, due to the driver's inattention, it leads to the vehicle slowly and gradually turning to a side lane, and then approaching to the lane boundary, which eventually leads to the vehicle departing from the original driving lane. The second is that the vehicle continues to drive in the lane and keeps normal following. In this case, the vehicle basically keeps parallel with the edge of the lanes, and it takes a long time for the vehicle to approach to and cross the lane line. The third is that the driver consciously changes lanes. In this case, according to traffic rules, drivers should turn on the corresponding turn signals to indicate the intention of changing lanes to the surrounding vehicles. The fourth is to drive the vehicles into or out of the expressway. In this case, the curvature of the road is generally large, and drivers often focus on slowing down (Liu et al., 2010).

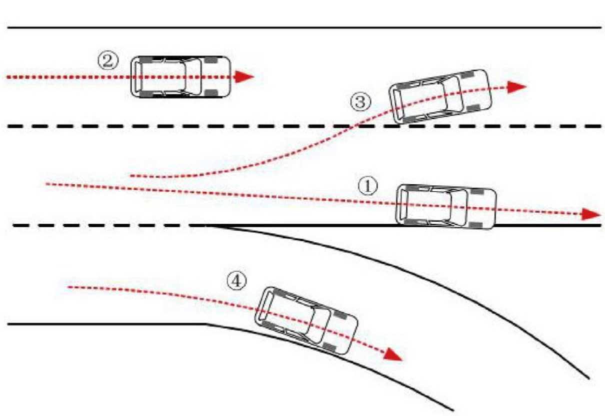

Fig. 2 – Vehicle road driving cycle model (Liu et al., 2010).

When the driver drives the vehicle unconsciously and gradually deviates from the current lane, LDWS can send warning signal to the driver before the departure of the lane to provide the driver with as much reaction time as possible, so as to greatly reduce the occurrence of traffic accidents caused by lane departure. At the same time, the development and application of LDWS can also effectively correct the bad habit of drivers not turning on the turn signal, and give early warning for lane departure caused by long-time driving or fatigue driving resulting in inattention. Deviation early warning signal includes sound warning, vibration warning, image warning and others. To a certain extent, these deviation early warnings can effectively reduce the occurrence of excessive fatigue driving, and then improve the safety of vehicle driving (Zhang et al., 2016; Zheng et al., 2018).

According to the research data of the Federal Highway Administration (FHWA), the use of LDWS can effectively avoid about 50% of traffic accidents caused by lane departure. The in-depth research and wide popularization of LDWS can greatly reduce the economic losses and casualties caused by traffic accidents. The popularization will be of great significance to improve road traffic safety. The relevant research data show that if the lane departure warning can be issued 0.5 s in advance, drivers can manipulate the vehicle to correct the direction of driving to avoid at least 60% of traffic accidents. Because of these reasons, LDWS has gradually become a focus of attention of researchers and the automotive industry (Chee and Lau, 2017; Wei et al., 2018).

LDWS can help drivers avoid or reduce traffic accidents caused by lane departure. It can be divided into two lane departure warning subsystems: longitudinal and horizontal (Fan, 2018). The longitudinal LDWS is mainly used to detect lane departure collision caused by too fast speed or out of control direction, while the transverse LDWS is mainly used to monitor the lane departure collision caused by drivers' inattention or drivers' abandoning steering operation (Jung and Kelber, 2005).

One of the main contents of this paper is the lateral LDWS based on monocular vision. Most LDWSs take the lateral position of the vehicle in the lane as a basis for calculating whether the warning occurs or not. These systems for detecting the lateral position of vehicles can be basically divided into two categories: road infrastructure system and vehicle-based LDWS (Jung and Kelber, 2005).

2.1. LDWS based on road infrastructure

The LDWS based on road infrastructure detects the transverse coordinate position of vehicles by means of road infrastructure (Jin et al., 2007; Wang et al., 2014). This system needs to transform the existing road. The most classic road reconstruction method is to use the magnet or wire buried under the road, and the vehicle driving on the road uses sensors to detect the ferromagnetic signal buried under the road, and calculate the signal strength, so as to determine the transverse coordinate position of the vehicle in the current lane (Aessandretti et al., 2007; Wang, 2017). The calculation accuracy of this method for the transverse coordinate position of driving vehicles can reach to several centimeters. Meanwhile, it is also obvious that the biggest drawback of this detection method needs to transform the existing road, which often costs a lot (An et al., 2013; Deng and Wu, 2018; Fan, 2018; Sheu et al., 2013; Xiao et al., 2020; Xu et al., 2020).

2.2. LDWS based on vehicle

The LDWS based on vehicle mainly uses machine vision/image processing or infrared sensor to detect the position of lane marking lines. According to the different installation positions of video acquisition equipment, the LDWS based on vehicles can be divided into side view system and forward looking system (Aziz et al., 2013). Side view system-the video acquisition equipment is installed on the side of the target vehicle and points to the side lane obliquely; forward looking system-the video capture device is installed in front of the target vehicle and is inclined to the lane ahead. The function modules of the side looking system and the forward looking system are basically the same. They are composed of three basic modules: vehicle and road state perception, lane departure decision-making algorithm, and warning signal sending. Whether it is a forward looking system or a side looking system, it first uses the state perception module to measure the geometry of the current road and the relevant dynamic parameters of the driving vehicle, and then applies the lane departure decision algorithm to evaluate the possibility of lane departure. If there is a trend of departure or a departure is occurring, it will send a warning signal to the driver (Long et al., 2015).

2.2.1. Side view system

The advantage of the side view system is that the system is simple and easy to employ and implement when the vehicle is driving on the structured road. Moreover, the execution efficiency of the system is particularly high, and it is also convenient to obtain higher positioning accuracy of driving vehicles; the disadvantage of the side looking system is that on unstructured roads, when lane identification line information is not clear or cannot be effectively identified, the accuracy and stability of the system will drop sharply (Pizzati et al., 2019).

Aurora system is the most representative system-based side looking system (Madrid and Hurtik, 2016). In 1997, the school of robotics at Carnegie Mellon University successfully developed Aurora system. Aurora system is mainly composed of the following three parts. One is color camera with wide angle lens; the other is digital converter; the third is portable Sunsparc workstation. Aurora system installed a color camera on the side of the target vehicle to detect lane markings on the side of the vehicle, and the visual field of the color camera is about 115–116 m long; then the system uses a digital converter to convert the camera signals and to collect video, and finally inputs the collected and converted video to the portable Sunsparc workstation for necessary processing. The processing frequency of this portable Sunsparc workstation is 60 Hz. The core processing algorithm in Aurora system consists of the following parts: (i) lane line detection and tracking based on machine vision; (ii) calculation and estimation of vehicle lateral coordinate position; and (iii) lane departure decision and warning. The Aurora system utilizes an adjustable standardized template to detect and identify lane markings. When tracking lane markings, it first detects whether there are lane markings in front of the current frame images. If no lane marking is detected, the system will carry out all line searching. When the Aurora system detects and determines the lane marking line, it will analyze the transverse coordinate position of the driving vehicle, which is the distance between the center of the driving vehicle and the lane marking line. Finally, a reasonable lane departure warning trigger mechanism is designed to form an effective communication mode between Aurora system and the driver, so as to avoid lane departure as much as possible. The advantage of the implementation of the side view system is that the theoretical method is simple and easy to implement, and the implementation effect is ideal on the highway with high degree of structure. It can simply and quickly calculate the position of the vehicle, and the positioning accuracy is high. However, Aurora system also has its fatal defects, and its application scope is relatively limited, so it can only be applied to structured roads with clear lane markings (Chen et al., 1995).

2.2.2. Forward looking system

Compared with the side looking system, the forward looking system has a lot of road information to use. It can be used normally even on roads without clear lane markings. Of course, it also has its defects, that is, the forward looking system is easy to be disturbed by other information in the front road image, such as pedestrians, other vehicles, road pollutants, etc., when determining the transverse coordinate position of the current driving vehicle.

2.2.2.1. Typical forward looking system. Forward looking system is a widely used LDWS. AutoVue, AWSTM, DSS, ALVINN, Scarf, JLUVA-1 systems, etc., are all representative forward looking systems (Li, 2015).

(1) DSS system

In 1998, Mitsubishi, a Japanese automobile design and production company, proposed to develop a DSS system. In the autumn of 1999, Mitsubishi automobile company installed the DSS system on the vehicle for testing. DSS system consists of the following basic functional modules: CCD camera, speed sensor, and visual and auditory warning devices. The DSS system uses the CCD camera installed in the front windshield and rear-view mirror to collect the road video in front of the vehicle, then applies the image processing technology to detect the lane marking lines in the image, carries on the mathematical model fitting to the detected lane marking lines, calculates the curvature half diameter, lateral movement speed and other related state parameters of the lane marking lines, computes and determines the driving vehicle by using the controller according to the relative position distance and cloud top speed of lane marking lines, analyzes whether the driving vehicle will gradually deviate from the original lane, calculates the time when it will cross the lane line, and analyzes whether the system will send out departure warning information combined with the threshold set in advance. If the calculated time of crossing the lane line is less than the threshold value set by the system, the DSS system will send warning information to the driver through visual, auditory and tactile means to remind the driver to correct the driving direction of the vehicle. It should be emphasized that there are some lane keeping assist systems in the DSS system, LKAS function, when the driving vehicle produces unconscious lane departure phenomenon, the DSS system will automatically generate a steering torque to drive the vehicle back to the correct lane. Of course, the steering torque generated by the DSS system will not interfere with the steering torque manipulated by the driver. That is to say, when a driver operates the vehicle to issue a special torque, the DSS system will automatically generate a steering torque to drive the vehicle back to the correct lane. The directional torque is automatically shielded to ensure the driver's absolute control over the driving vehicle (Benligiray et al., 2012; Gackslatter et al., 2010).

(2) Jluva-1 system

The system is developed by the intelligent vehicle research group of Jilin University in China in 2008. The system is based on monocular vision. It is mainly composed of vehicle power supply, embedded microcomputer, display equipment, black and white CCD camera, data line, speaker and image acquisition card. The system uses the CCD camera installed in the rear-view mirror to collect the road images in front of the vehicle, and obtains the position parameters of the vehicle in the current lane through image processing. Once it detects that the vehicle is too close to the white line in its own lane, it may deviate into the adjacent lane, and the driver has not turned on the turn signal, the system will send a warning message to remind the driver to correct the unintentional so as to reduce the occurrence of lane departure accidents as much as possible.

(3) Embedded lane departure alarm system based on DSP

It was developed by Southeast University in China before 2009. It is composed of A/D conversion and decoding circuit module, buffer circuit module, media processor DSP circuit module, encoding and D/A conversion circuit module. The system collects the analog video signal of the tracked lane line through the vehicle mounted camera, generates the digital signal stream buffer after decoding, and sends it to the video interface of high-speed media processor DSP. Then, the video processing module extracts the lane characteristic value of the digital video signal, and finally sends the processed video signal to the encoding and digital to analog conversion circuit output display (Dong, 2004; Yu et al., 2009).

(4) ALVINN system and Scarf system

Carnegie Mellon University in the United States has the more in-depth study on intelligent transportation system engineering. Its Automation System Research Center (VASC) and Navlab Laboratory of robotics college jointly developed the lane departure warning systems ALVINN and Scarf. ALVINN system uses neural network to learn correct behavior from a large number of training data. Scarf system divides the collected road images into road pixels and non-road pixels according to their colors. Meanwhile, due to the characteristics of video images captured by cameras, assuming that the actual road presents a trapezoidal field view in each of the collected images, it searches for the best road position in the image with the help of Hough transform. Since the trapezoidal shape field composed of road pixels is searched in Scarf system, the system cannot be applied in the case of multi lanes (Gaikwad and Lokhande, 2015; Tseng and Lin, 2013).

(5) AutoVue system

In June 2000, Iteris company of the United States and Daimler Chrysler company of Germany jointly developed and applied AutoVue system for the first time. Up to now, many brands of trucks in Europe have popularized the AutoVue system as an option. The U.S. government is also actively promoting the application of AutoVue system to reduce the probability of traffic accidents caused by lane departure. The system is mainly composed of the following functional modules: (i) the video acquisition equipment installed in the rear-view mirror of the driving vehicle; (ii) the software of the lane line detection, identification and tracking; (iii) the speaker and display equipment; and (iv) the control system unit. AutoVue system calculates the relative position of the driving vehicle in the current lane in real time by analyzing the road image acquired by the video capture device, and also analyzes the distance between the driving vehicle and the lane identification line. Then, according to the alarm threshold set in advance in the system, it analyzes whether the vehicle is about to or is in the process of lane departure, and judges whether to send out warning information. When the system calculates that the driving vehicle is about to deviate from the current lane, it will send a rumbling warning tone to the driver to prompt the driver to adjust the driving direction and position of the vehicle in time. The advantage of AutoVue system is that it has strong environmental adaptability and can work effectively and stably in most different climate environments (Obradovic et al., 2013; Park et al., 2015).

(6) AWSTM system

The AWSTM system is studied and developed by a company named Mobileye in Israel. The system is installed in the video acquisition equipment on the front windshield of the driving vehicle. It detects the lane lines on each road image obtained by the video capture equipment, analyzes and calculates the relative position between the driving vehicle and the current lane line, and computes the distance from the lane marking line. AWSTM system can detect different types of lane marking lines, such as dashed line, double solid line, solid continuous line, etc. If there is no obvious lane marking line on the road, it can detect the boundary of the road to analyze the vehicle position and determine whether to send warning message of lane departure to the driver. The lane departure decision warning module of AWSTM system is to identify the road boundary, analyze the relative position between the driving vehicle and the lane marking line, and calculate the time when the vehicle is about to cross the lane boundary by using the lateral movement speed of the vehicle. If the time of crossing the boundary is lower than the preset threshold, the system will send out warning information to remind the driver to avoid traffic accidents, hence the driver should correct the direction of the vehicle in time. It can set different warning thresholds to use the driving characteristics of different groups of people. It will block the warning information when the driver controls the vehicle for lane departure with his own will, or has braking behavior, or there are no clear road signs or lane marking lines. In particular, it also takes into account the drivers' driving behavior. In the case of no significant lane marking line, the system can detect the boundary of the road for lane departure warning, and can also work normally at night, in rainy days and other adverse weather conditions (Navarro et al., 2017; You et al., 2015).

2.2.2.2. Current multiple function early warning systems. Recently, a number of companies in the world have developed the advanced driver assistance systems (ADAS) based on vision, which can prevent and reduce the occurrence of traffic accidents with the "eye of science and technology". The system includes multiple functions, and the lane departure warning is one of them. The followings are such two typical systems that have a large market in the world.

(1) ADAS system by Mobileye in Israel

After fifteen years of hard research and development by more than 200 researchers in Mobileye company in Israel, it has developed the world's active safety product ADAS. According to company data in 2017, there are nearly one million cars using the system (Denton, 2019; Kim et al., 2016; Riener, 2010).

The ADAS system consists of two key parts: high resolution vision sensor and eyewatch Gamma visual display. The vision sensor is a small black box mounted inside the windshield of the vehicle. It has a visual sensor inside and provides a real-time audible warning to the driver, and the eyewatch Gamma visual warning is provided. The main monitoring items of ADAS is as follows.

(a) Front collision warning: when the vehicle is about to collide with the vehicle in the front, the system will send out an early warning signal.
(b) Vehicle departure warning: the system will issue a warning when the vehicle deviates from the lane without proper signal notification.
(c) Pedestrian and bicycle collision warning: when the vehicle is about to collide with pedestrians or bicycles, the system will issue a warning.
(d) Headway monitoring and warning: warning when the vehicle is in danger of the next driving.
(e) Speed limit indicator: it can automatically identify the speed limit sign, and the system will give a warning when the vehicle speed exceeds the limit.
(f) Intelligent high beam control: according to the light intensity and the relative distance with other vehicles, the system automatically turns on/off the high beam light.

Mobileye also plans to launch Israel's first driverless autonomous car Hailing service early next year. The technology will be implemented in phases, first in a small pilot area, and then the business is planned to be extended to all areas of Israel by 2023. Mobileye also plans to pilot test driverless vehicles in the United States and China.

(2) Star system in South Korea

The Star ADAS system consists of lane recognition sensor, lateral angular velocity sensor, front steering actuator and controller. The lane recognition sensor is mainly composed of black-and-white camera and image processing components. The camera is installed at the rear-view mirror of the cab and points to the front lane. Its main function is to identify lane marking lines, road curvature radius, lateral offset and heading angle. The main function of the lateral angular velocity sensor is to detect the yaw rate of the vehicle. The front steering actuator is mainly composed of hydraulic power steering mechanism. Its main function is to apply a certain amount of torque to the steering mechanism according to the command of the controller to make the steering wheel rotate at a certain angle. The main function of the controller is to calculate the deviation between the actual and expected driving tracks of the current vehicle, and issue warning command and steering actuator control command when necessary.

Recently, Hyundai Kia automobile of South Korea has decided that, starting from next year, all cars produced in South Korea, except taxis and buses, will be equipped with anti-collision warning system as standard. As Hyundai Kia's market share in South Korea has reached to 80%, Shuanglong, Renault and Samsung will follow suit. It is predicted that by 2020, all new cars produced in South Korea will be equipped with this configuration.

The research of LDWS mainly focuses on the vision-based system. However, from the existing technical level, the most important factors affecting the reliability of the vision-based LDWS are the weather conditions of the system application and the influence of light changes, which is a major problem faced by all vision-based systems currently. At present, it is the development trend of all vision-based lane departure warning systems to study various robust lane departure evaluation algorithms which can adapt to various weather conditions and overcome the influence of light changes and shadow conditions.

In 2015, the authors of this paper tested and compared the above two different systems. They used the same car and drove in the same road for about 40 km. For the worn lane line road, the ADAS system by Mobileye is better than Star system. If the worn lane line road is more than 30–40 m, it is difficult to accurately estimate the lane by Star system, but Mobileye ADAS system can work well. When we meet a vehicle in a cross suddenly, Star system acts more slowly than Mobileye ADAS system. In conclusion, the systems, the algorithm detection accuracy and speed are different.

Hence, no matter which system in the above presented, the key point and hard task is to accurately and quickly detect lane lines in a traffic video. Therefore, a huge number of vision-based algorithms/methods for lane line detection have been studied by different researchers and organizations. The algorithms/methods are related to different sensors or their combination. The traditional algorithms/methods are mainly studied and developed based on image processing and computer vision techniques, which have been researched for three decades, and some of them have been implemented into the above systems. Since the traditional ones cannot meet the industrial or system requirements, the 3D processing algorithms with multiple sensors and the semantic segmentation methods including deep learning and neural network have been studied in recent years. The following sections are for the algorithms/methods description and analysis.

3. Status of lane line detection based on image processing and computer vision

The lane detection is first realized by traditional image processing and computer vision algorithms. Although the traditional method has been gradually replaced by the semantic segmentation methods such as deep learning method in recent years, many of the traditional method/algorithm design ideas and details are still worthy of reference and learning. So, this section will start from the traditional image processing and computer vision algorithms/methods.

In traditional image processing and computer vision methods, the lane line detection algorithms are mainly divided into five steps as shown in Fig. 3 (Liu, 2014; Shirke and Udayakumar, 2019). The first step is image acquisition, where the selection of the camera type and resolution is important for the further image processing. At present, whether in academic or industrial level, the automatic driving is the main focus of computer vision and robot technology research. No matter what kind of scheme, all kinds of sensors and control modules are needed to sense the environment around the vehicle. The lane detection based on camera is an important method of environment perception. It can make the vehicle locate correctly in the lane. At the same time, it is also important for the subsequent lane departure or trajectory planning. Therefore, the accurate lane detection based on camera is the key factor to achieve the full automatic driving.

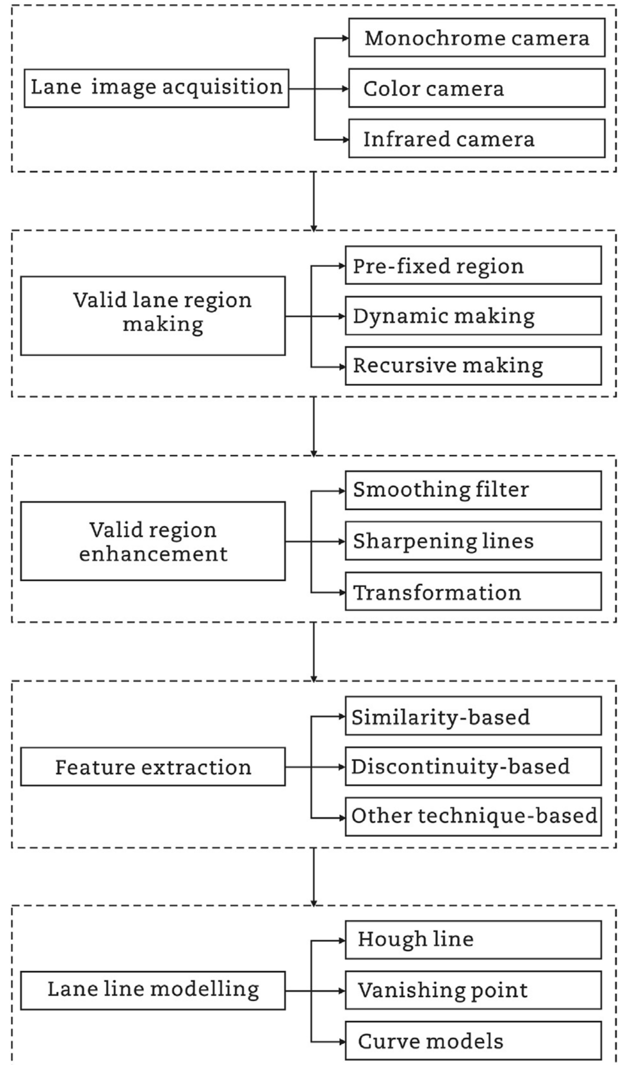

Fig. 3 – General working procedure for lane line detection by image processing.

The second step is to decide which region is the valid lane detection region for avoid noising and image processing complex. In the most cases, the valid region can be presented as Fig. 4; but in some cases, however, the valid region may be variable in the driving (Yu et al., 2017), e.g., when the vehicle is going from a one-lane road to a multi-lane road, the region may needs to be wider; when driving from daylight to night time, the region length and width many be changed, as shown in Fig. 5 (Lin et al., 2010). Anyhow, this variation will be changed based on the changes of road condition and lighting on road. The last three steps are to detect lane lines by different image processing algorithms, and we will discuss those in the follows.

3.1. *Lane image enhancement*

In the third step, the image in the valid region is pre-processed by image smoothing, sharpening, etc., to increase image quality for lane line feature extraction. The algorithm design and development should be based on image characteristics,

Fig. 4 – Regional division of lane image in general.

e.g., for the night images, fog images, or shadow images, the enhancement algorithm should be different (Kortli et al., 2017; Küçükmanisa et al., 2019; Yoo et al., 2013).

The enhancement algorithm selection is important in this step. As shown in Fig. 6, a vague image is enhanced by five different algorithms: (i) exponential transformation makes image darker, but the contrast between lane lines and other parts is increased; (ii) logarithm transformation makes image lighter, but the lane lines are still vague; (iii) image equalization result is better than the former two results, but the top part of the image is still vague; (iv) dark channel prior-based algorithm (He et al., 2009; Tsai et al., 2019) enhances the image colors and contrast, but the lane lines are still unclear in the top part of the image; and (v) retinex-based algorithm (Zhang et al., 2018) makes the contrast between lane lines and other parts increasing, but the color is not enhanced well.

In some cases, the camera lens will have some distortion, mainly including radial distortion and tangential distortion. It is needed to correct the distortion before lane detection, and it is more conducive to scene detection. If the geometry correction of coordinate mapping between image and camera is involved, it can also provide more accurate conversion. Of course, for the wide-angle, fisheye and other lenses, such errors might be ignored.

In addition, to make lane line detection easily, some image transformation is needed, for example, the image can be transformed into inverse perspective mapping (IPM) (Wang et al., 2014). IPM transform has two advantages. On the one hand, it can reduce the amount of calculations, but it will inevitably lose some feature information. On the other hand, the lane lines in bird eye view are basically close to parallel lines, and the line extraction can be better completed through the shape restriction of lines. One example is shown in Fig. 7 (Choi et al., 2018).

3.2. *Feature extraction algorithms*

The fourth step is image feature extraction. The algorithms based on image features mainly use the characteristics of the lane line shape, pixel gradient, and color features in the image to detect the lane lines (Joshy and Jose, 2014; Zhou et al., 2010). The basic process based on the feature extraction is to convert the image into a grayscale image first, and then extract lane region or edge feature information. This kind of algorithms can be classified into the similarity-based and discontinuity-based ones.

3.2.1. *Similarity-based algorithms*

For extracting lane lines based on similarity, a simple algorithm is thresholding (Gonzalez and Ozguner, 2000). The thresholding algorithm can be global or dynamic. A global algorithm requires that each of the detecting image has the similar gray scale histogram (Hu et al., 2020), but it is impossible in most cases (Zhang, 2017). Fig. 8 gives the lane line image histograms for different cases.

In a road lane image, the proportion of lane marking lines is relatively small, and it is difficult to produce "double peaks" features in a gray scale histogram, in which the lane marking lines can be extracted. In addition, with the existence of other kinds of different interference information, it is hard to directly use a global thresholding algorithm to detect and process the lane marking line images. As shown in Fig. 8, the lane line images and their histograms in different cases, such as the images taken in shadow occlusion, night, rainy and haze weather, are displayed respectively. It can be seen that their histograms are completely different (Zhang, 2017).

According to the lane marking line images and their corresponding histograms under several typical conditions in Fig. 8(a) and (b), it can be found that although there are clear lane lines in the image under normal illumination even with shadows, the proportion of lane lines in the image may be relatively small, which leads to the absence of lines in the

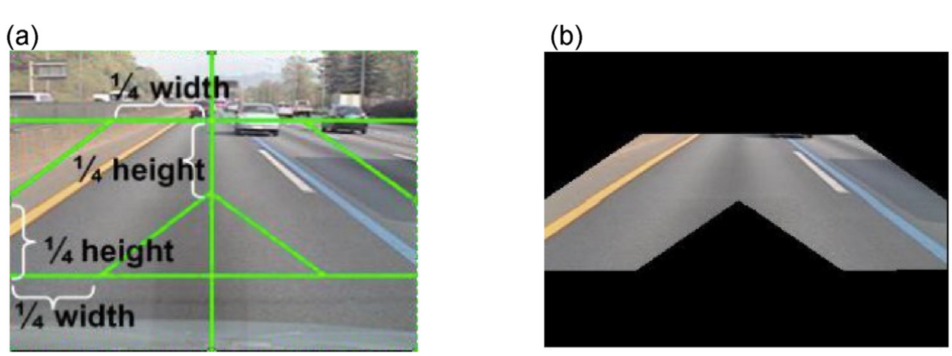

Fig. 5 – Regional division of lane image in special (Lin et al., 2010). (a) Road view range mark. (b) Lane regions.

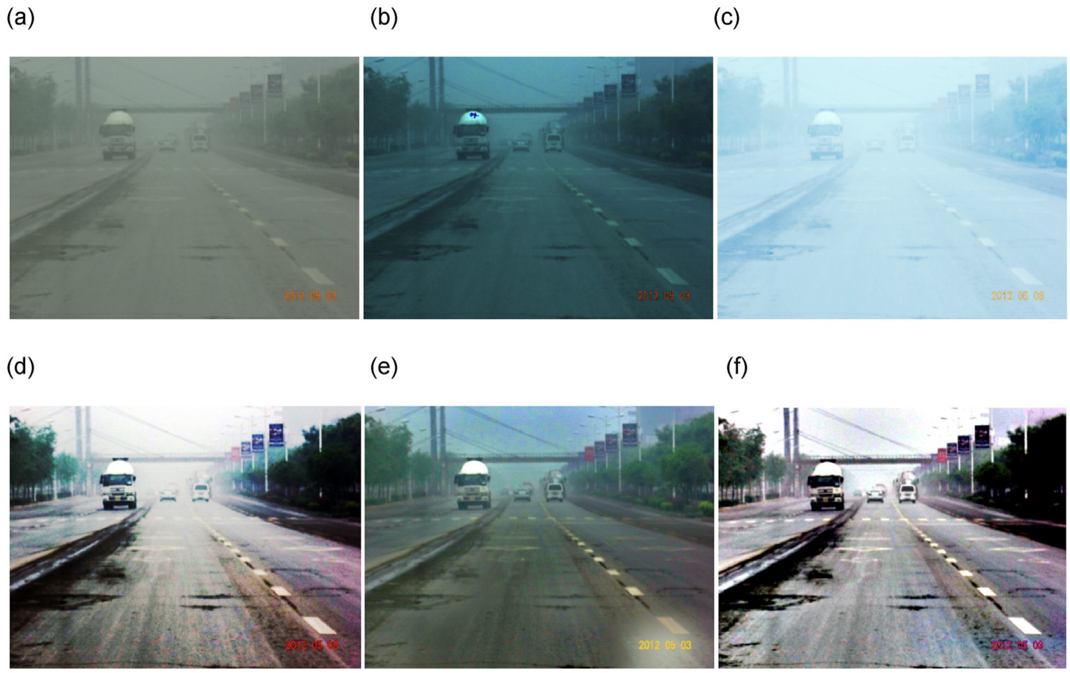

Fig. 6 – Comparison of different image enhancement algorithms for a vague lane line image. (a) Original image. (b) Exponential transform. (c) Logarithm transform. (d) Histogram equalization. (e) Dark channel prior. (f) Retinex.

histogram and is characterized by "double peaks". In the case of tree shadow occlusion, although there are obvious "double peaks" features in the image histogram, the "double peaks" is generated by the shaded and non-occluded parts of the road, which cannot represent the characteristics of lane marking lines in the image. Fig. 8(c) and (d) presents the lane image in a rainy day and the corresponding histogram. Due to the interference of water, reflection and other noises, the corresponding histogram has no significant characteristics or "bimodal" features; no matter what threshold it is, the lane lines cannot be extracted. Fig. 8(e) and (f) shows the night time road image and its histogram. Similar to Fig. 8(b), although there are "double peaks" in the histogram, the "double peaks" is generated by the part with strong light and the part with weak light; the lane lines may be mixed in the strong light part, and it is difficult to be identified by a threshold. Fig. 8(g) and (h) shows the road image in a hazy or foggy day and its histogram. Through actual measurement,

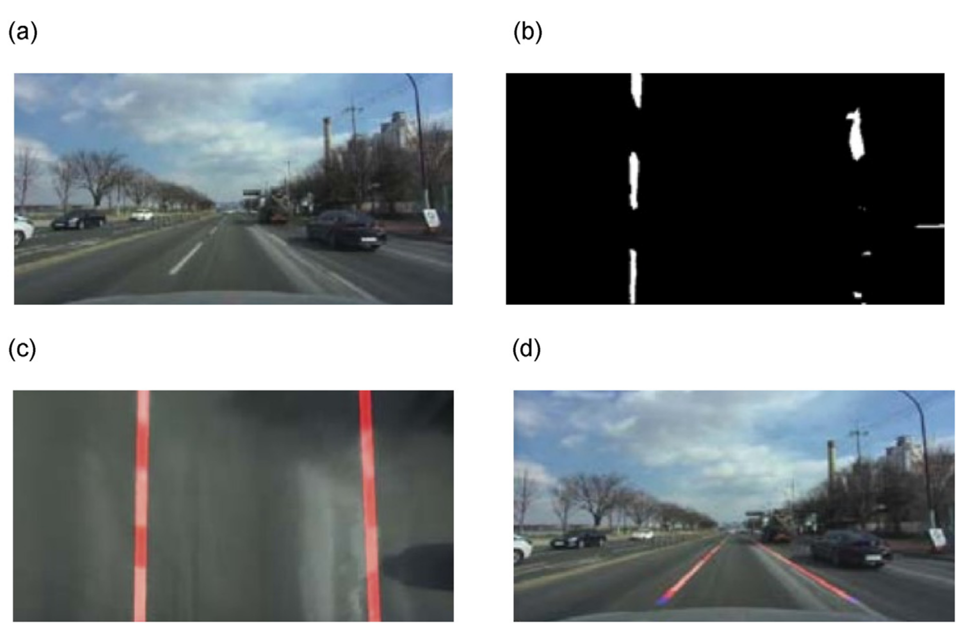

Fig. 7 – Lane line detection procedure (Choi et al., 2018). (a) Original image. (b) Edge IPM image. (c) Lane parameter result. (d) Final detection result.

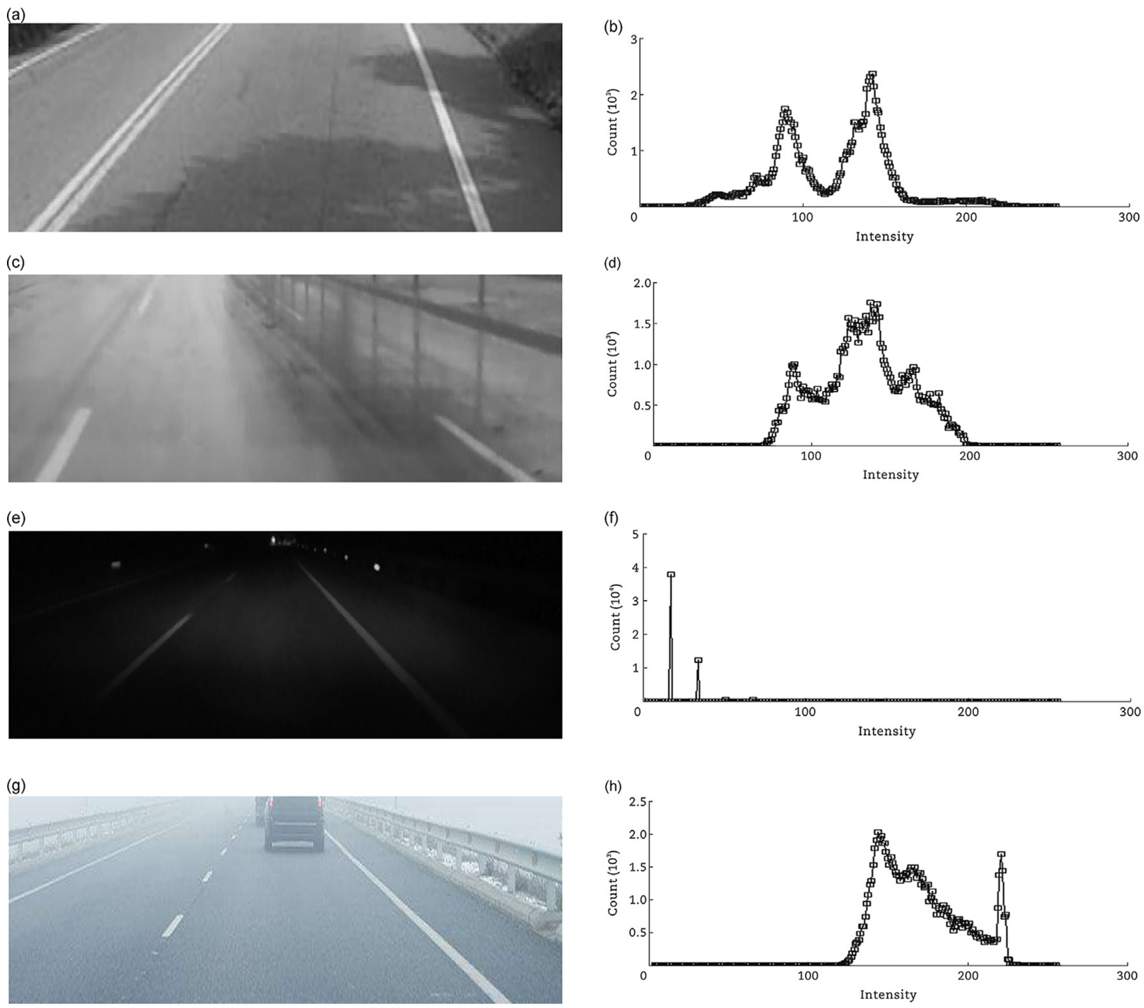

Fig. 8 – Different histogram shapes for different road lane line images (Zhang, 2017). (a) Image in shadow occlusion case. (b) Histogram in shadow occlusion case. (c) Image in rainy weather. (d) Histogram in rainy weather. (e) Image at night time. (f) Histogram at night time. (g) Image in foggy or hazy weather. (h) Histogram in foggy or hazy weather.

the pixel values of lane marking lines are in a wide range of 200–210, and the "double peaks" feature in the histogram is not produced by the lane marking lines.

In a word, in a lane line image, because the area proportion of lane marking lines is relatively small, and the interference information and noise characteristics under different road conditions are different, it is difficult to generate significant features or "double peaks" structure related to lane marking lines in the corresponding histogram, which makes it hard to facilitate the detection of lane marking lines with a global thresholding algorithm.

Instead of that, dynamic thresholding algorithms (Yu et al., 2017) or other region similarity algorithms (Kortli et al., 2017; Küçükmanisa et al., 2019) might be suitable for some special situations. For instance, the color can be the cue for lane line extraction (Chiu and Lin, 2005); the random finite set can be used in the lane line detection (Deusch et al., 2012); the distance transform is applied to find lane lines (Jiang et al., 2011); and the fuzzy math is utilized into the image segmentation (Madrid and Hurtik, 2016; Obradovic et al., 2013). Gupta and Merchant (2016) made an approach for automated lane detection by using K-means clustering, the effect of which depends on the road and weather situations, making it not suitable to complex situations; even the situation is not too complex, the algorithm has to be combined with other algorithms. As shown in Fig. 9, the original image was taken at night without other vehicles; after clustering, most part of lane lines are extracted, but it needs more processing operations by some post functions. For more extended similarity-based algorithm study, Ma et al. (2018) researched an algorithm based on optimized dense disparity map estimation for multiple lane detection. As shown in Fig. 10, the algorithm firstly maps the road surface, and then makes the lane line detection. In Fig. 10, the regions in green are estimated road surface areas and the lines in red are detected lanes.

3.2.2. *Discontinuity-based algorithms*

For extracting lane line edge information, after the above image enhancement, it is often to use different edge detectors

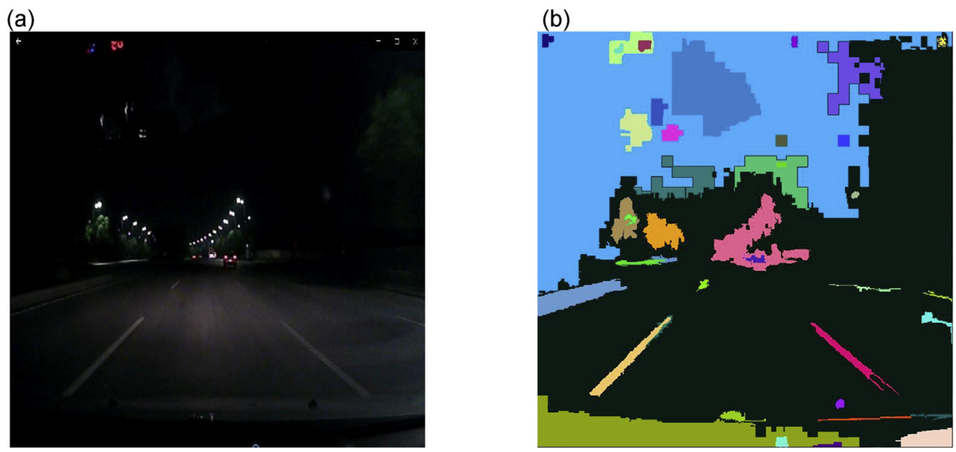

Fig. 9 – Lane line detection by using *K*-means clustering. (a) Original image. (b) *K*-means clustering result.

firstly, such as Canny (Li et al., 2016), fractional differential (Zhang, 2017), Gabor (Zhou et al., 2010), Sobel and Laplacian operators, and some special operators (Baili et al., 2017; Deng and Wu, 2018). This kind of algorithms has fast calculation speed and strong scene adaptability, but it is susceptible to interference from light and obstacles, resulting in the large deviations in the detection results.

After edge detection, to make lane line edge sharper, some image enhancement procedures are added, e.g., Yoo et al. (2013) did the gradient enhancement for uneven-illumination images to make robust lane line detection. After image binarization, since the lane line edges are discontinuous, for instance, Benligiray et al. (2012) and Ozgunalp et al. (2017) studied an algorithm for tracing the lane lines based on the vanishing point estimation; Son et al. (2014) also did the similar procedure for lane line tracing; Niu et al. (2015) made the two-stage feature extraction with curve fitting; and Tan et al. (2014) assumed each lane line as a river filled based on gradient information.

Due to the complexity of the road environment, there are usually some buildings or street views on both sides of the road, thus the lane line detection is easy to be affected by uneven illumination and the shadow of trees. In a procedure, Zhang (2017) selected two typical road images, and then used her algorithm to detect lane lines, as shown in Fig. 11. Firstly the fractional integral is used to denoise; then the maximum inter class cross entropy and fractional differential are used to extract lane lines; subsequently the improved least square method is applied to fit the lane lines; finally the lane lines are connected based on vanishing points.

It can be seen from Fig. 11 that when the brightness of road lane image is low or the edges of lane lines are unclear, the image enhancement is needed. To avoid affecting by no-lane regions, the part with lane lines at the bottom of the original image is cut off as a new image; after the fractional integral is applied to remove the noise and preserve edges, the lane line extraction algorithm based on the maximum inter class cross entropy and fractional differential is applied to get the more obvious lane edges; finally, based on vanishing points, the improved least square method is adopted to fit the lane lines and connect line segments to get the continuous lane lines.

Another similar example is the algorithm by Son et al. (2014). They studied an algorithm for detecting the vanishing points of lane lines according to the voting space. It defines an adaptive region of interest to reduce the computational complexity, and then uses different color attributes of lane lines to realize the lane line detection in the candidate regions with the constant illumination. Finally, the selected lane lines are clustered. Fig. 12 shows the original lane line image (resolution: 304 × 191 pixels). The line segments are made by a ridge edge detection algorithm and the lane line extraction result by Son et al. (2014). As presented in Fig. 12, the original image includes three obvious straight lane lines with different colors, the detection results are satisfactory, and the algorithm result depends on the detected candidate lane line points and the curvature.

Fig. 10 – Experimental results (Ma et al., 2018).

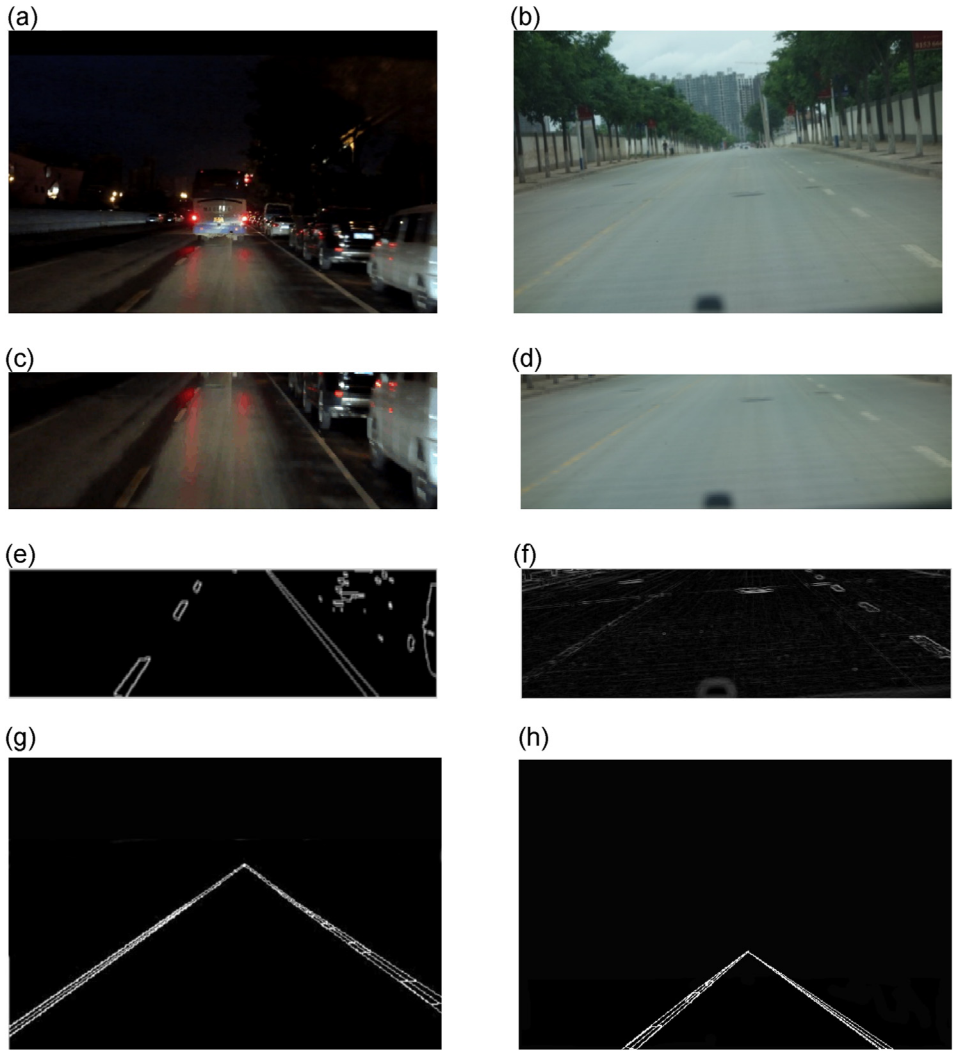

Fig. 11 – Lane line detection (Zhang, 2017). (a) Original image 1. (b) Original image 2. (c) Cut image 1. (d) Cut image 2. (e) Fractional differential image 1. (f) Fractional differential image 2. (g) Vanishing point result 1. (h) Vanishing point result 2.

Another way for detecting the lane lines is to utilize the Hough straight line transform. A huge number of researchers have applied the Hough transform into the lane line detection. Yi et al. (2015) proposed driver assistant system, in which a camera is mounted on the vehicle front window to detect the lane lines roughly; then the Hough transform is applied to identify the lane lines. Zhang et al. (2018) studied a lane line tracking algorithm based on an improved Hough traight line transform. Fan (2018) proposed an improved algorithm based on the Hough straight line transform, in which the edges are detected and grouped in an image, and the Hough transform is adopted to identify the lane lines. Wei et al. (2018) suggested a lane line detection method based on the constraint Hough transform double edge extraction, in which the lane line area extraction is made based on the lane width feature and color feature; then the Canny edge detector is used to obtain the lane line edges and the lane line features are extracted through the lane line edge and area information; finally the straight lane lines are identified by a modified Hough transform. Deng and Wu (2018) used a double lane line edge detection method in light on the constraint condition Hough transform to detect lane lines. Baili et al. (2017) simplified the process of edge detection by using a horizontal differentiating filter, and then the detected edge points were grouped into lines with a modified Hough transform.

As one simple example, based on the image in Fig. 12(b), the Hough straight line transform parameters are selected as: angle step threshold is 1, distance threshold step is 1, the thresholds of number pixels in a line are 49, 45 and 43, respectively. From Fig. 13, there are three different detection results which depend on the threshold selection. Therefore, Hough transform is unstable for straight lane line detection, and it is dependent on the parameter selection.

In addition, a lane line is not a straight line in some cases, so the straight line fitting algorithms are not suitable for all the cases. Hence, some researchers used some curves to fit the lane lines (Jung and Kelber, 2005; Niu et al., 2015), but the lane line fitting is also depending on lane line point detection results.

Fig. 12 – Algorithm for detecting the vanishing points of lane lines (Son et al., 2014). (a) Original image. (b) Binary image. (c) Algorithm result.

3.3. *Model-based algorithms*

A number of researchers studied model-based algorithms for lane line extraction, e.g., the above described vanishing point and Hough transform also belong to model algorithms in the binary image processing. Line fitting usually adopts Hough transform combined with group lines. Of course, one can also try to replace Hough transform with a line segment detector (LSD) and other line detection algorithms, but it doesn't make sense. The curve fitting can be directly fitted by quadratic or cubic function, but it needs to make some constraints on the head and tail, otherwise it is easy to fly off. Because of the complexity of road model, the image of camera perspective is transformed by perspective. Thus, if the head and tail are required to fit specially, the regular linear function may have inherent limitations, and spline curve is generally utilized to fit. Bertozzi and Broggi (1998) made a stereovision system for generic obstacle and lane detection. Tseng and Lin (2013) also made lane line regression by using 3D model. López et al. (2010) and Zhou et al. (2010) applied some geometric models to identify lane lines.

Ma et al. (2000) made the simultaneous detection of lane and pavement boundaries using model-based multisensor fusion. Lee (2002) proposed a machine vision system for lane-departure detection. The model-based detection method is to fit the lane through the curve model (Jiang et al., 2011). Commonly used curve models are the following: linear, parabolic, spline, etc. (Shirke and Udayakumar, 2019). Compared with other feature information, the lane line has obvious line characteristics, and it can be detected combined with the Hough transform algorithm to search the position of the lane line in the image (Wang et al., 2010; Wei et al., 2018); also, it can use the appropriate curve model to fit the lane line and draw the final conclusion. In the detection method using the lane model, the disappearance of feature points and noise interference have little effect on the algorithm effect, but the simple straight line model is difficult to describe a variety of lane lines. Jung et al. (2015) did lane line detection based on spatiotemporal images. The complex curve model calculation method is sensitive to noise points. It is difficult to adapt to the changing vehicle driving environment (Wang, 2017; Zhang and Ma, 2019). With the rapid development of computer vision based on convolutional networks, the ability to extract lane line features has been significantly improved compared to traditional image processing algorithms. Ye et al. (2018) made the development and evaluation of lane hazard prediction application in a model-based method.

For the mode-based algorithms, there is a typical example by Shin et al. (2015). They used multiple particles from a single image line into a super particle, adjusted the detected boundary points by using local linear regression, and detected left and right lanes respectively by two independent particle filters. This method can be applied to a variety of complex road background as they reported, and can detect curves. Fig. 14(a) and (b) respectively shows the original image and lane line extraction result by their method.

Traditional lane line detection algorithms based on image processing rely on highly specialized manual feature marking and heuristic recognition to identify lane lines (Deusch et al., 2012; Hur et al., 2013; Jung et al., 2013; Tan et al., 2014; Wu et al., 2014). This manual marking method is mainly based on color features (Chiu and Lin, 2005), structural tensor (Loose et al., 2009), strip filter (Teng et al., 2010), ridge feature (López et al., 2010), etc., which may be combined with Hough transform or Kalman filter (Kim, 2008; Li, 2020; Zhang, 2017). After the lane line is identified, the post-processing technology is used to filter out the false detection to form the final lanes. Usually, these traditional methods are easy to cause robustness problems due to the change of road scene. Some other model many be setup based on personal

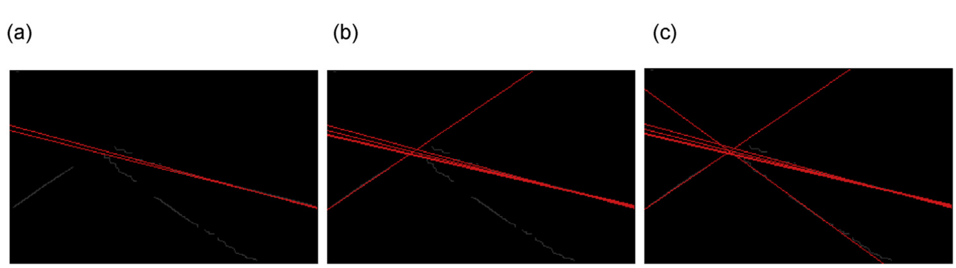

Fig. 13 – Hough transform with different parameters based on Fig. 12(b). (a) At least 49 pixels in each line. (b) At least 45 pixels in each line. (c) At least 43 pixels in each line.

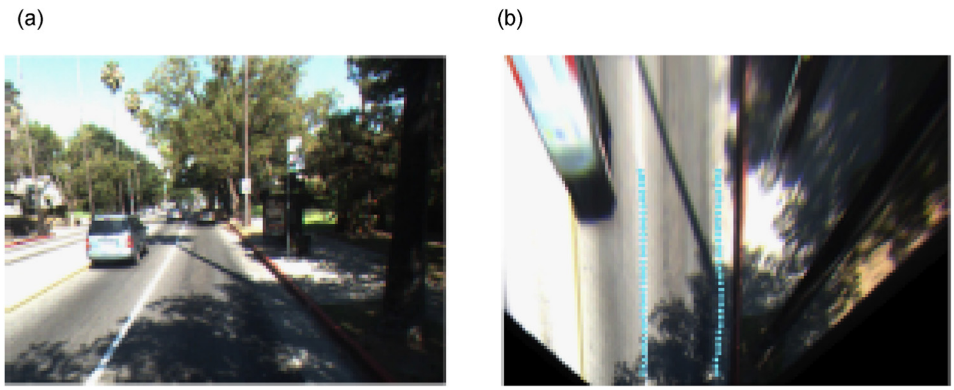

Fig. 14 – Lane line detection by Shin et al. (2015) method. (a) Original image. (b) Detection result.

(Wang et al., 2018). Although the algorithms of the lane line detection in image processing and computer vision has been studied for three decades, some of the algorithms are mostly suitable for some special situations, thus it is hard to expand one algorithm into wide applications. The more precision the lane line detection needs, the more complicated the algorithm will be; hence the method based on image processing and computer vision will be replaced by the recently studied semantic segmentation method.

4. Status of the lane line detection based on semantic segmentation network

Semantic segmentation network is a model based on neural network and deep convolution network. Its most basic task is to classify different kinds of pixel points in the image, and aggregate the same kind of pixel points, so as to distinguish different target objects in the image (Smirnov et al., 2014; Xing et al., 2020; Zou et al., 2020).

In 2014, Berkeley University suggested the full convolutional network (FCN), which opened the door to the study of deep convolutional network in the field of semantic segmentation (Long et al., 2015). The method replaces the fully connected layers in the classification convolutional network with convolutional layers, and it fuses information on different scales through a layer-jump structure to get semantic inferences on the image content. In light on the foundation of the FCN, more and more researchers made more network structures based on different applications. In 2015, the encoder-decoder structure was proposed in the SegNet network (Long et al., 2015), so that more decoding stage information was introduced in the decoding process, and the semantic content was more accurately segmented. The suggested network makes the semantic segmentation network as an end-to-end model. In the model, it is suggested to use pooling to perform the upsampling operation, which effectively improves its computing efficiency.

The dilated convolution operation was introduced in the U-net model structure that appeared later, which can further increase the local receptive field and gather multi-scale information without reducing the dimensions. In the DeepLab V1 network, the proportion of expansion convolution is further increased, and the conditional random field (CRF) model is added to the adjacent pixel relationship reasoning. After that, the DeepLab series network has been developed continuously, with many improved versions, and the backbone network has been also used such as the DeepLab V3+ network (Li, 2020).

In the segmentation task for the lane line scene, the pixels belonging to the lane line in the road scene need to be merged and detected. The lane line detection task is usually solved using a semantic segmentation model. At present, relevant researchers and institutions have proposed many different deep network models for this task, which can be basically divided into three types based on convolutional neural network (CNN) network model, decoder-encoder structure model, and the combination of CNN and recurrent neural network (RNN). There are some other methods, such as regions with CNN features (RCNN) (Chanu et al., 2020).

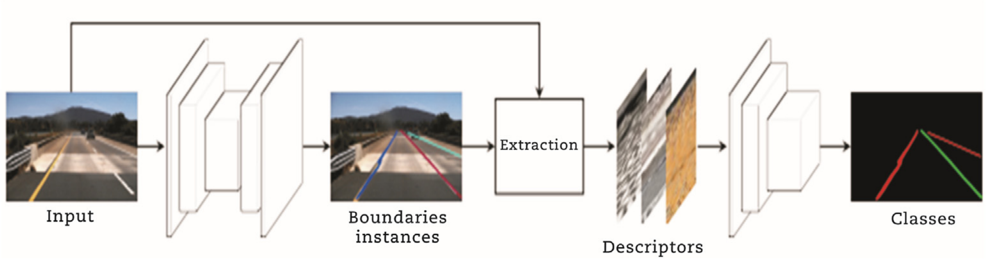

Fig. 15 – Cascaded CNNs network model (Pizzati et al., 2019).

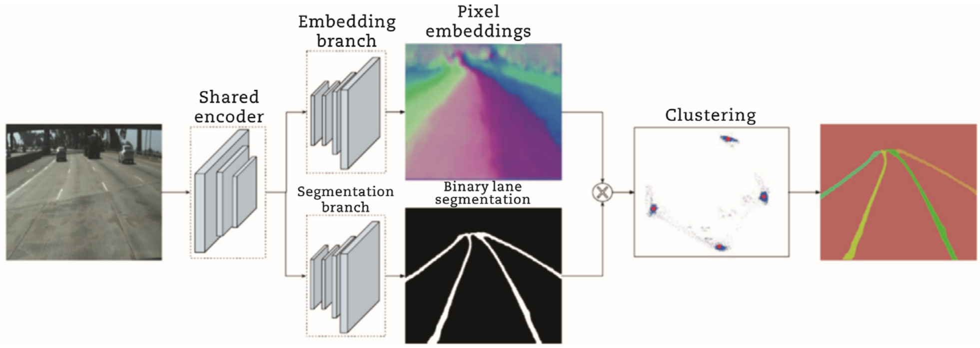

Fig. 16 – LaneNet network structure (Neven et al., 2018).

4.1. *Lane line detection based on CNN network model*

Long et al. (2015) and Pizzati et al. (2019) divided the task of lane line segmentation into two stages. In the first stage, the efficient residual factorized ConvNet (ERFNet) network is used as the basic model to semantically segment the input image, and the segmentation result will be obtained in the later stage (Romera et al., 2018). Scene images are classified, and images containing lane feature lines are output. The model is divided into two stages on the TuSimple dataset: the semantic segmentation network is trained first, then the classification network is trained, and finally the results are output. The overall structure of the model is as shown in Fig. 15.

4.2. *Lane line detection based on encoder-decoder model*

The encoder-decoder is an end-to-end model. The model can directly output the segmentation result through the data input. The lane line detection network LaneNet (Neven et al., 2018) is based on the improvement of SegNet, which has two decoder structures. A decoder is a segmented channel used to detect lane line features in a binary mask. The other is the embedded channel, which is utilized to fit the road. By combining the results of the segmentation channel and the embedded channel, the clustering method is used to finally fit the contour of the lane lines. The network structure is shown in Fig. 16.

The output of LaneNet is the pixel set of each lane line, and a lane line needs to be regressed according to these pixels. The traditional method is to project the image into the aerial view, and then use quadratic or cubic polynomial fitting. In this method, the transformation matrix is only calculated once, and all the images use the same transformation matrix, which will lead to errors under slope changes.

4.3. *Lane line detection based on CNN and RNN combined model*

The characteristics of the lane lines of urban roads have certain continuity. Combining the characteristics of the CNN and RNN methods can effectively use the timing information in the video. In the literatureby Zou et al. (2020), the lane line video is first segmented into small time sequence feature maps through the convolutional network, which are sent as input into long short-term memory (LSTM) network for processing of feature images, and finally the output is sent to the CNN network for upsampling to output the final semantic segmentation result. Before the cyclic network, the U-net network pre-trained on the ImageNet dataset is applied for time series feature extraction, and after the cyclic network, the SegNet network pre-trained on the ImageNet dataset is used for lane line feature extraction. Through the combination of CNN and RNN to train the continuous time frame data, the result is better than that obtained by utilizing CNN model alone. The network structure is shown in Fig. 17.

In the algorithm for driver intention inference system, which focuses on the freeway lane change maneuvers, firstly, a high-level driver intention mechanism and framework is introduced (Xing et al., 2020); then an inference system of vision-based intention is suggested, which can capture the multi-modal signals in light on multiple low-cost optical cameras and the VBOX vehicle data taking system, in which, VBOX data taking systems are utilized for measuring the speed and position of a moving vehicle. Based on a range of high-performance GPS receivers, VBOX data loggers can record high accuracy GPS speed measurements, distance, acceleration, braking distance, heading, slip angle, lap times, position, cornering forces and more. A new ensemble bi-directional RNN model with LSTM units is proposed to deal with the driving sequence of time-series and the temporal behavioral patterns. Naturalistic freeway driving data that consists of lane-keeping, right and left lane changing maneuvers are collected and utilized for model construction and evaluation. Furthermore, the driver's pre-maneuver activities can be statistically analyzed. It is found that for situation-aware, drivers usually check the mirrors for more than six seconds before they initiate the lane changing maneuver, and the time interval between steering the hand wheel and crossing lane is about two seconds on average. Finally, the hypothesis testing is conducted to present the significant improvement of their algorithm over existing ones. With five-fold cross-validation, their model achieves an average accuracy of 96.1% for the intention that is inferred 0.5 s before the maneuver starts.

4.4. *Lane line detection based on CNN and RANSAC combined model*

Kim and Lee (2014) introduced a lane detection method based on CNN with the random sample consensus (RANSAC)

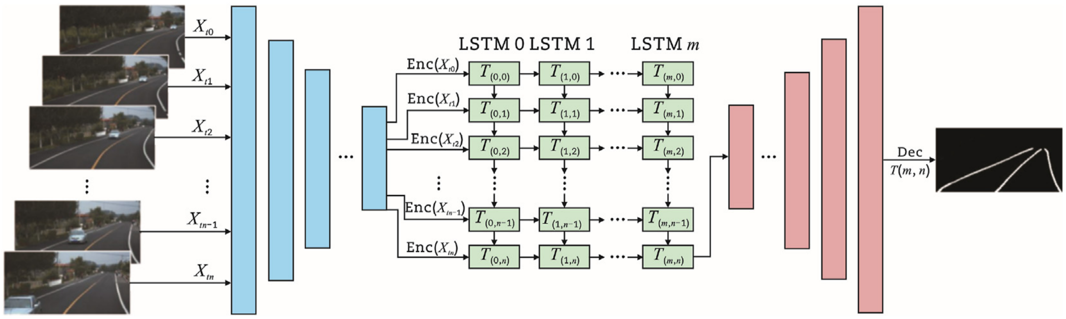

Fig. 17 – CNN and RNN combined network model (Zou et al., 2020).

algorithm. Firstly, the algorithm calculates edges in an image using a hat shape kernel, then detects lanes using CNN combined with RANSAC. If the road scene is simple, the lane can be detected by using the RANSAC algorithm only. If the road scene is complex and includes roadside trees, fences, intersections, etc., it is difficult to detect lanes due to noisy edges. To alleviate the problem, the authors used CNN in the lane detection before and after applying the RANSAC algorithm. In the training process of CNN, the input data consist of the edge images in a region of interest and target data become the images those have only drawn real white color lanes in black background. The CNN structure consists of 8 layers with 3 convolutional layers, 2 subsampling layers and multi-layer perceptron including 3 fully-connected layers. Convolutional and subsampling layers are hierarchically arranged and their arrangement represents a deep structure in deep learning. As a result, their algorithm successfully eliminates noise lines, and the performance of lane detection is found to be better than other ordinary line detection algorithms such as RANSAC and Hough line transform. Fig. 18 shows the examples of lane line detection by using the algorithm. This algorithm is able to detect lane markers that are in the shadow as well as parallel, broken and scattered markers.

4.5. *Lane line detection based on DeepLab V3+ network model*

Li (2020) studied the DeepLab V3+ network, where the weight matrix generated by the attention structure module was fused into the feature map to obtain the final feature maps with weight characteristics. The fusion feature maps were segmented by semantic information to obtain the lane line segmentation image. The comparative experiments were tested on public datasets to verify the feasibility and stability of the proposed model. A density clustering algorithm was made to cluster the lane line feature points in the segmentation graph, which can describe the lane line features more effectively and eliminate the misclassification of pixel points in the semantic segmentation network. Aiming at the problems of current lane line confirmation and structure disappearance, the least square method was utilized to carry out linear fitting merging of current lane lines, and the Kalman filter was applied to predict and track the current lane lines.

In the verification set, the lane line images were selected under different conditions such as curvilinear lane lines, missing left lanes, missing right lanes, no obvious lane markings, insufficient lighting, obstruction, etc. In Fig. 19, the

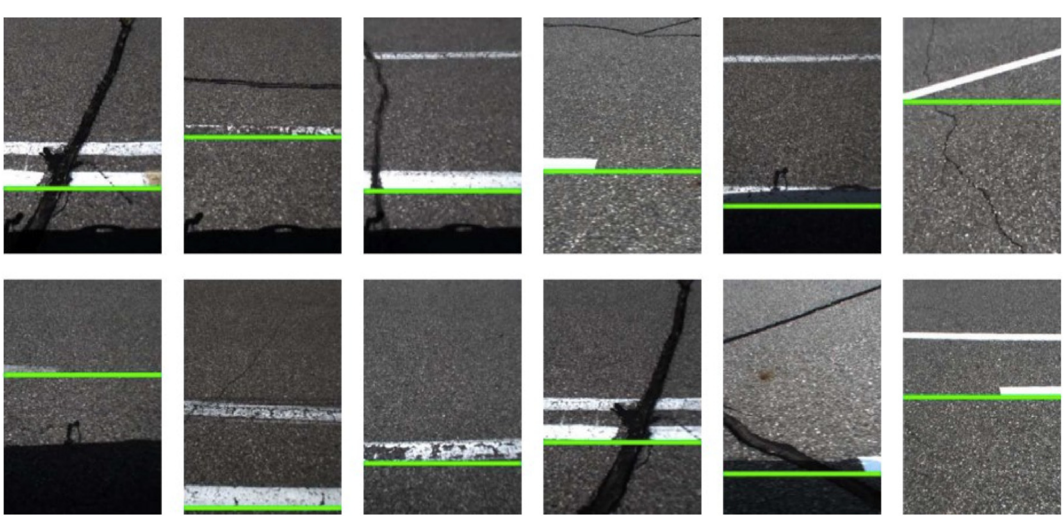

Fig. 18 – Lane line detection based on CNN and RANSAC combined model (Kim and Lee, 2014).

Fig. 19 – Experimental results based on TuSimple data test set (Li, 2020). (a) The first group of lane line images. (b) Correct marking of lane lines in the first group of images. (c) Lane line semantic segmentation maps in the first group of images. (d) The second group of lane line images. (e) Correct marking of lane lines in the second group of images. (f) Lane line semantic segmentation maps in the second group of images.

two sets of experiments were conducted for the above situations. Fig. 19(a) and (d) is for the original drawings of lane lines; Fig. 19(b) and (e) is for the correct lane line marks based on the original drawings; and Fig. 19(c) and (f) is the results of semantic segmentation, where the lane lines will be described with different color lines (Li, 2020).

From the experimental results, it is found that in most cases, the model has good detection ability and generalization

Table 1 – Comparison of test results of different models (Li, 2020).

Dataset type	Method	Recall rate (%)	Accuracy (%)
Straight set	ENet	75.5	73.4
	SCNN	95.2	93.2
	DeepLab V3+	95.4	93.4
	Method of this paper	95.8	94.8
Corner set	ENet	71.2	70.5
	SCNN	94.0	93.5
	DeepLab V3+	94.2	93.0
	Method of this paper	95.5	94.5
Worn lane set	ENet	70.2	69.5
	SCNN	93.8	91.5
	DeepLab V3+	92.8	90.6
	Method of this paper	93.5	92.8
Night environment	ENet	40.5	38.0
	SCNN	70.5	68.1
	DeepLab V3+	71.2	65.0
	Method of this paper	65.5	62.4

ability. For example, in Fig. 19(a), the lane lines, even with the missing left lane or the missing right lane, and with the obviously degraded lane line markers, can be effectively detected. Also, it can get accurate results for a certain degree of reflective scenes. For some scenes with many obstacles, the road edges or road passing through the bridge deck, there are some false detection situations, which will mistakenly judge the edge of the obstacles as the edge of the lane line. In the second image in Fig. 19(b), it clearly mistakenly judges the edge of the bridge. In the third image in Fig. 19(b), it is obvious that the lane line mark cannot be higher than the lane plane, which is inconsistent with the prior knowledge and the semantic segmentation is wrong. In general, the network based on DeepLab-LatNet's semantic segmentation can effectively detect lane lines in common scenes, and can accurately detect some lane lines marked with dashed lines or the areas where some lane feature marks are missing (Li, 2020).

In order to better evaluate the performance of the model, several classic deep learning models are selected and compared. The specific performance is shown in Table 1. The selected models are ENet network (Paszke et al., 2016), spatial CNN (SCNN) network (Pan et al., 2018), and DeepLab V3+ network (Li, 2020). The ENet network is a semantic segmentation network with high real-time performance in mobile scenarios. It has the characteristics of detection speed block, few network parameters, and the ability to run on mobile devices. SCNN network is a semantic segmentation network designed for lane line scene. In this model, the part of the convolution layer is replaced by the component slice structure, so that the information can be transferred across rows and columns, and more context information is integrated, which is suitable for continuous structure and large target detection. DeepLab V3+ network is mainly compared with the attention structure proposed by Li (2020).

It can be found from Table 1 that ENet network is mainly targeted at real-time scenarios and has few learning parameters, and the segmentation results for this scenario are poor compared to others. The SCNN network structure is close to the DeepLab V3+ network in performance, and both can effectively identify the lane lines in the test samples. Compared with DeepLab V3+, the accuracy of the method (DeepLab V3+ network) has been slightly improved. It can effectively detect the scenes involved in the dataset, but it is greatly affected by the night environment lighting effect, resulting in the decline of detection accuracy. The analysis result shows that due to the comprehensive influence of various light sources such as neon lights and street lights in the urban night environment, the attention network structure has caused certain misjudgments to the lane area, resulting in a lower overall detection success rate (Li, 2020).

4.6. *Lane line detection based on 3D network model*

Anyhow, recently, a lot of researchers studied semantic segmentation methods for lane line extracting. Mukadam et al. (2017) made tactical decision making for lane changing with deep reinforcement learning. Mirchevska et al. (2018) studied high-level decision making for safe and reasonable autonomous lane changing using reinforcement learning. Hoel et al. (2018) and Luo et al. (2020) researched the automated speed and lane change decision making using deep reinforcement learning. Neven et al. (2018) suggested towards end-to-end lane detection: an instance segmentation approach.

In recent years, with information technique development, 3D information detection technology has been used in the road traffic (Wang et al., 2020c). To resolve lane line detection under more complicated situations, Garnett et al. (2019) and Kim and Park (2017) studied a method based on 3D-LaneNet: end-to-end 3D multiple lane detection. Guo et al. (2020) made Gen-LaneNet: a generalized and scalable approach for 3D lane detection. The newly three examples are as follows.

(1) Multi-lane detection based on instance segmentation and attentive voting

Chang et al. (2019) proposed a multi-lane detection model-based algorithm by using instance segmentation and attentive voting, which outperforms state of the art methods in terms of both accuracy and speed. The authors also offered a dataset with a more intuitive labeling scheme as compared to other benchmark datasets. By using the method, they were able to obtain a lane segmentation accuracy of 99.87% running at 54.53 fps (average) as reported. The proposed model can predict the precise points of lane lines smaller than the input image size, and can distinguish each pixel of each instance. The control value can be modified by detecting other lane lines. The wrong picking will change the control value quickly, reliability, bias and characteristics. The confidence and bias can predict the points on the lane lines, and the eigenvalues can distinguish which instance each prediction point belongs to. Finally, it is through the application of post-processing module to eliminate outliers and generate smooth lane lines.

They gave four conclusions. (a) The output image size of the method is smaller than that of the instance segmentation method, and the compact size can save the memory of the

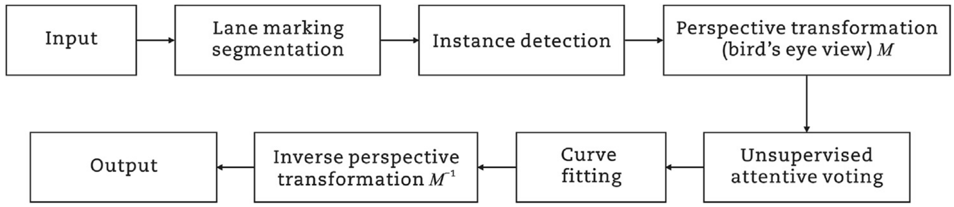

Fig. 20 – Architecture diagram of multi-lane detection based on instance segmentation and attentive voting (Chang et al., 2019).

module. (b) Since it adds post-processing module, the method can eliminate outliers. (c) It can be used in various scenes, and can predict any number of lane lines in any direction, vertical or horizontal. (d) The evaluation results show that the false detection rate of this method is lower than that of other methods. Their architecture diagram is presented in Fig. 20, and the processing result examples are listed in Fig. 21.

(2) Key points estimation and point instance segmentation model

Ko et al. (2020) suggested a novel lane detection method for the arbitrary number of lanes using the deep learning method, which has the lower number of false positives than other recent lane detection methods. The architecture of their method has the shared feature extraction layers and several branches for the detection and embedding to cluster lanes. The method can generate exact points on the lanes, and they cast a clustering problem for the generated points as a point cloud instance segmentation problem. Their method is more compact because it generates fewer points than the original image pixel size. Their post processing method eliminates outliers successfully and increases the performance notably. The current implemented version, however, requires a lot of computing cost as they reported. Their method framework is presented in Fig. 22. Given an input image, PINet predicts three values: confidence, offset, and feature. From confidence and offset outputs, exact points on the lanes can be predicted, and the feature output distinguishes the predicted points into each instance. Finally, the post processing module is applied, and it generates smooth lane. The processing result examples are listed in Fig. 23.

(3) Semi-local 3D lane detection and uncertainty estimation model

Efrat et al. (2020) suggested a new method which is based on the assumption that complex lane lines can be approximated by locally linear line segments. Semi local is an important concept in their study, that is, the image is divided into grids, and each grid is classified into two categories (to judge whether the line passes through). In addition, the physical meaning of the horizontal offset, angle and height offset of the linear grid regression line is shown in Figs. 24 and 25. In order to connect the line segments into the whole lane line, the idea of clustering-based instance segmentation is used for reference, and that is to learn the characteristics of each grid. The features of

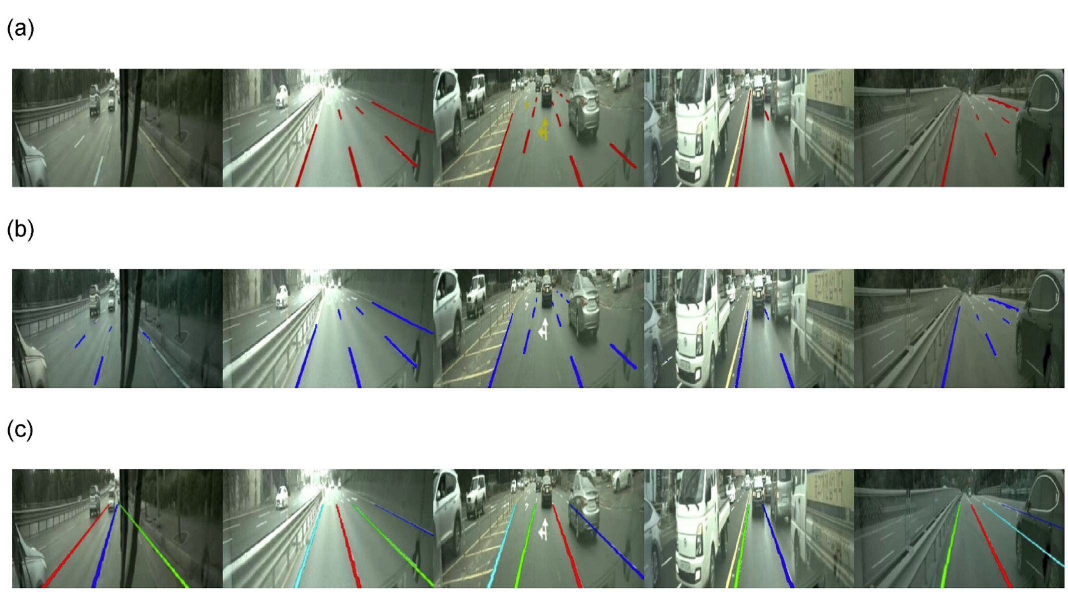

Fig. 21 – Visual results (Chang et al., 2019). (a) Original input with ground truth. (b) Output of lane segmentation network. (c) Final output of attentive voting and curve fitting.

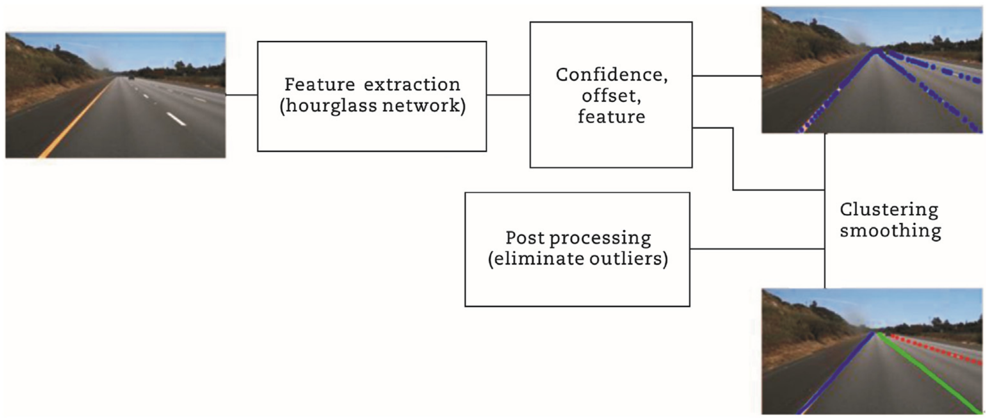

Fig. 22 – The proposed framework (Ko et al., 2020).

the same lane line should be similar, and the features of different lane lines should be different.

Their model and method framework are demonstrated in Figs. 24 and 25 respectively, and the processing result examples are shown in Fig. 26. In Fig. 26, it is clear that the surface geometries and curvatures appear in the test set are different from the train set. The detected lanes are shown in blue and 3D-LaneNet lanes in cyan. In Fig. 24, it is a camera-based 3D lane line detection with uncertainty estimation network. Their method works in bird eye view perspective, which is rasterized to the coarse tiles grid; the output parametric 3D curve is the representation for all tiles, which are then processed to form entire 3D lane curves together with the detection uncertainty estimates (Efrat et al., 2020). In Fig. 25, the network consists of two processing pipelines: image view (top) and bird eye view (bottom). The image view encoder is comprised of resnet blocks, each one multiplying the number of channels. The bird's eye view (BEV) backbone consists of projected image view feature maps those are concatenated with the convoluted projected feature map from the former block. The final decimated BEV feature map is the input for the lane prediction head that outputs local lane segments, global embedding for clustering the segments to entire lanes, and the lane point position uncertainty relying on both the local tiles and the entire lane curves (Efrat et al., 2020).

4.7. *Summary*

In recent studies, deep learning and neural network is used to replace manual marking, and a certain number of learning intensive feature detectors are constructed to predict, that is,

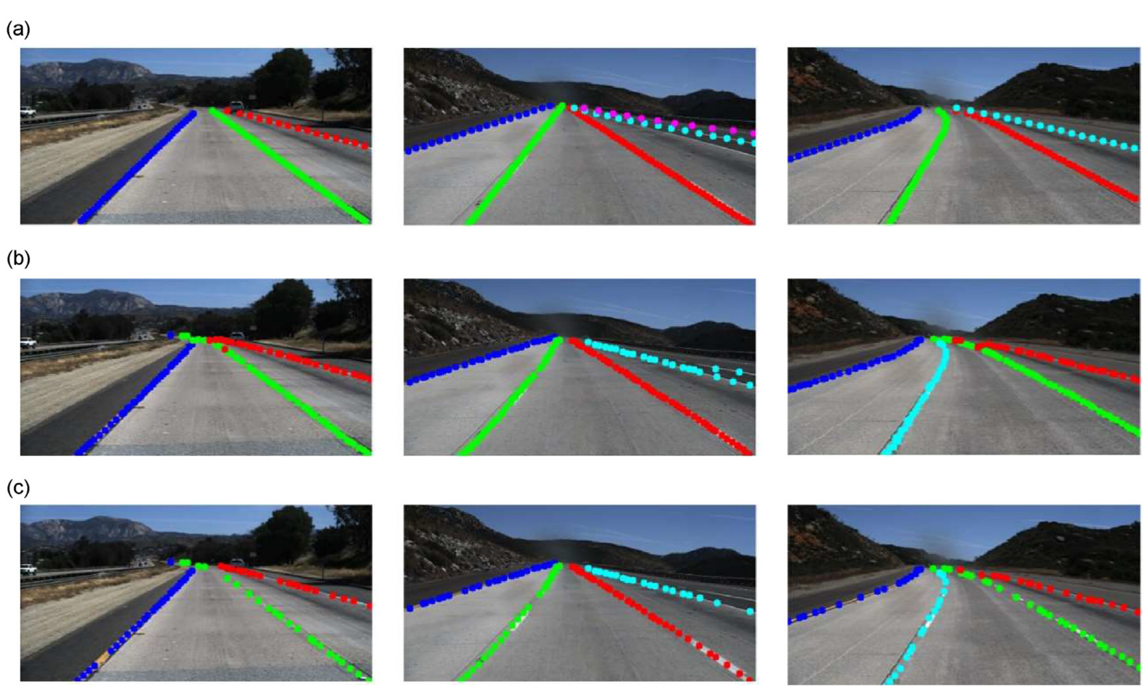

Fig. 23 – The results on the TuSimple dataset (Ko et al., 2020). (a) Ground truth data. (b) Raw outputs of the proposed network. (c) Final outputs after post processing.

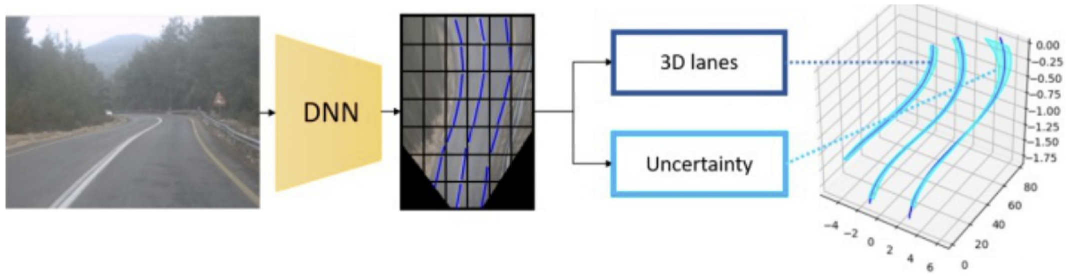

Fig. 24 – Processing model (Efrat et al., 2020).

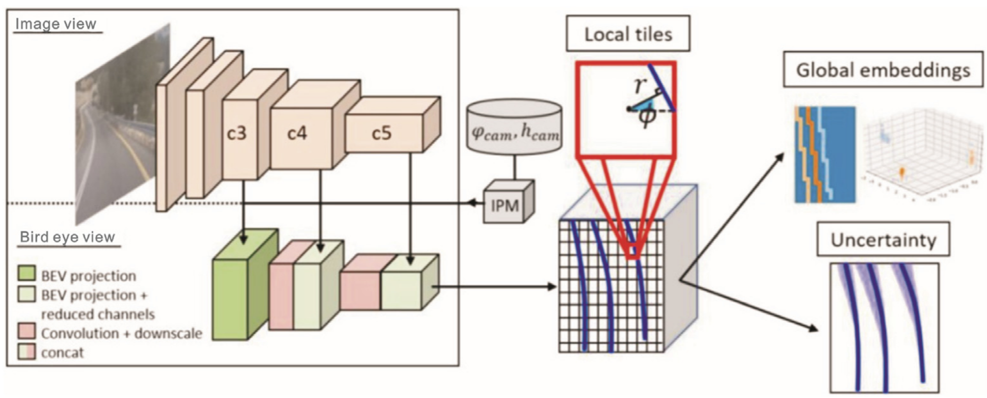

Fig. 25 – Framework of the method (Efrat et al., 2020).

pixel level lane segmentation. Gopalan et al. (2012) used pixel level feature descriptors to model and use enhancement algorithms to select relevant features for lane marking detection. Similarly, Kim and Lee (2014) combined CNN with RANSAC algorithm to detect lane lines. Note that in their methods, CNN is mainly used for image enhancement, and only when the road scene is complex. Huval et al. (2015) used CNN model for highway driving, including lane line detection and end-to-end CNN classification. Li et al. (2017) proposed the use of multi task deep convolution network,

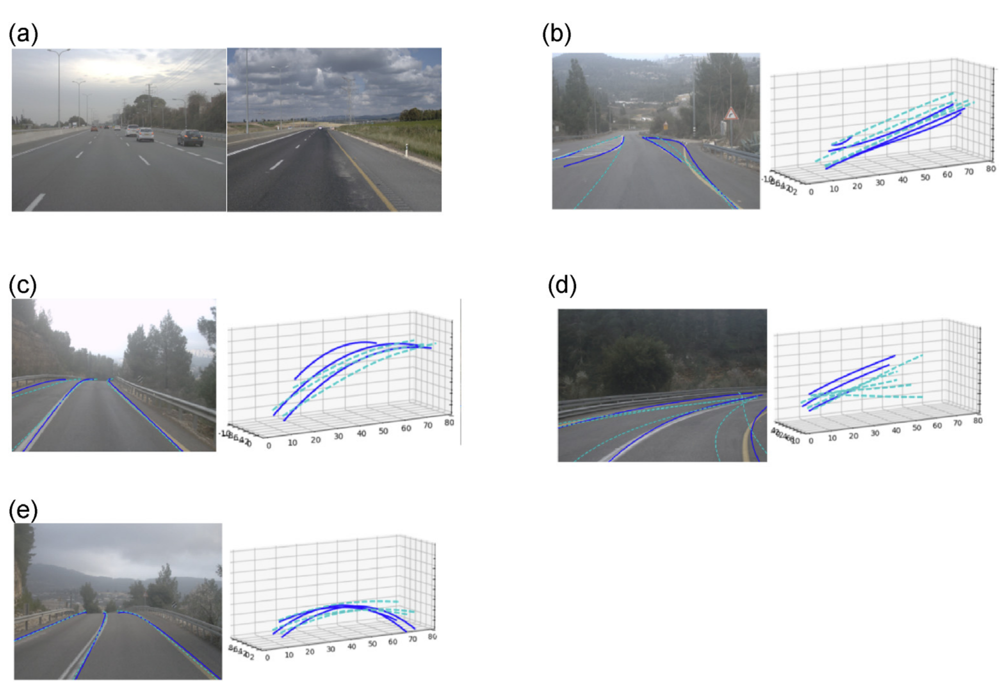

Fig. 26 – Examples of 3D-lanes (Efrat et al., 2020). (a) Examples from the training set. (b) Example 1 from the test set. (c) Example 2 from the test set. (d) Example 3 from the test set. (e) Example 4 from the test set.

which focuses on finding geometric lane attributes, such as location and direction, and cyclic neural network for lane detection. Lee et al. (2017) did more researches and they used deep neural networks to train how to jointly process lane and road marking detection and recognition under adverse weather and low illumination conditions. In addition to the ability to better divide lane line markers, the above neural network models can also estimate lane lines when there are no markers in the image. However, the generated binary segmented lanes still need to be decomposed into different lane instances. The deep learning method is new, and it has more advantages than the traditional vision-based algorithms, but the training set should be large enough to set the model for the accurate and quick lane line identification, which is the hard problem. The deep learning should be developed based on multiple sensors and the advantages of traditional image processing algorithms.

5. Conclusions

The research of LDWS mainly focuses on the vision-based lane departure warning system. However, from the existing technical level, the most important factors affecting the reliability of the vision-based LDWS need to be investigated, therefore there is still a lot of work to do for LDWS research and development. The following lists five problems in today's lane departure warning system.

The first problem is the bad weather factor. In most cases, the weather conditions vary a lot and the influence of light changes is complicated, which is a major problem faced by all vision-based systems. At present, it is the development trend of all vision-based LDWS to study various robust lane departure evaluation algorithms which can adapt to various weather conditions and overcome the influence of light changes and shadow conditions. Based on the development trend of automobile active safety and some complex traffic situations, the industry of automobile active safety electronics is gradually forming an independent system.

The second problem is that vehicles affect each other on the road. Multiple vehicles on the road often interfere with the identification of lane markings in LDWS, thus some LDWS systems will detect other vehicles (especially white vehicles) driving near the lane marking lines as part of the lane marking lines, which will cause the detected lane marking lines to deviate from the original correct direction. At the same time, if the other vehicles block most of the lane identification lines in the detecting image, it is likely to cause failures of lane line detection and extraction.

The third problem is system action speed. LDWS is a real-time operation system, which requires the real-time performance. It only starts warning when the vehicle reaches to a certain lane line departure threshold. If the speed of the vehicle is 100 km/h, the vehicle will travel about 30 m in one second. In one second, the on-board video capture device can obtain 20–30 road images. If LDWS cannot process every image in time, then get lane marking lines and give necessary warnings, it may put the vehicles in danger. LDWS should meet the requirements for the high accuracy, real-time and robustness, which is also a key contradiction of LDWS.

In addition to annoying, in some special time period, LDWS cannot work normally, which directly reduces the enthusiasm of users. In the United States, traffic accidents caused by lane departure mainly occur at 12:00 a.m. and 6:00 a.m. These two periods are the "disaster areas" of drunk driving and fatigue driving. At this time, once the vehicle lane departure occurs, even if the early warning system alarms in time, it is difficult to avoid the occurrence of disasters (Navarro et al., 2019). In addition, many drivers have lost the ability to control the steering wheel because of stroke, epilepsy and other diseases (Navarro et al., 2017). LDWS can only serve as a warning, unable to control the vehicle to return to the correct route, and finally it can only watch the tragedy unfolds.

The last problem is about the alarm system. The setting of alarm time in LDWS also plays an important role in the user experience of the system. The general alarm algorithm considers the relative coordinate position of the vehicle and lane marking lines, but it does not consider the driving habits of the driver, the vehicle trajectory and the relative movement trend of the vehicle and lane marking lines; LDWS will also give an alarm when there is no lane departure. In addition, because the detection results of the front module are not ideal, it will also cause the situation of alarm leakage. Whether frequent false occurs or not, the user's experience of LDWS will be poor and the trust degree of users on LDWS will be reduced.

To overcome the above problems and increase both the accuracy and speed of LDWS, the further research should focus on the following five aspects: (1) the fusion of multiple sensors can obtain more road information, which can get the detailed point view from different directions; (2) the 3D detection methods/algorithms need to be studied further, which can increase lane detection reliability; (3) the classification of adverse weather and road situation by using a special method/algorithm can be used for guiding right lane line detection routines; (4) the deep learning method has more advantages than the traditional vision-based algorithms, but the deep learning should be developed based on the traditional image processing algorithms; and (5) to increase the users' enthusiasm, in addition to increase LDWS reliability, the work procedure should be changeable according to the classification of adverse weather and road situation.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

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REFERENCES

Aessandretti, G., Broggi, A., Cerri, P., 2007. Vehicle and guard rail detection using radar and vision data fusion. IEEE Transactions on Intelligent Transportation Systems 8 (1), 95–105.

An, X., Shang, E., Song, J., et al., 2013. Real-time lane departure warning system based on a single FPGA. EURASIP Journal on Image and Video Processing 2013 (1), 38.

Aziz, T., Horiguchi, Y., Sawaragi, T., 2013. An empirical investigation of the development of driver's mental model of a lane departure warning system while driving. IFAC Proceedings Volumes 46 (15), 461–468.

Baili, J., Marzougui, M., Sboui, A., et al., 2017. Lane departure detection using image processing techniques. In: 2nd International Conference on Anti-cyber Crimes (ICACC), Abha, 2017.

Bartolini, A.E., 2015. Audio Cueing and Negative Adaptation in Older and Younger Drivers Using Lane Departure Warning Systems (Master thesis). University of Toronto, Toronto.

Benligiray, B., Topal, C., Akinlar, C., 2012. Video-based lane detection using a fast vanishing point estimation method. In: 2012 IEEE International Symposium on Multimedia, Irvine, 2012.

Bertozzi, M., Broggi, A., 1998. GOLD: a parallel real-time stereo vision system for generic obstacle and lane detection. IEEE Transaction Image Processing 7 (1), 62–81.

Chang, D., Chirakkal, V., Goswami, S., et al., 2019. Multi-lane detection using instance segmentation and attentive voting. In: 19th International Conference on Control, Automation and Systems (ICCAS), Jeju, 2019.

Chanu, M.M., Lourembam, R., Thongam, K., 2020. A deep learning approach for object detection and instance segmentation using mask RCNN. Journal of Advanced Research in Dynamical and Control Systems 12 (SP3), 95–104.

Chee, W., Lau, P.Y., 2017. A framework for lane departure warning system for various lane markings. In: 2017 International Workshop on Advanced Image Technology, Penang, 2017.

Chen, Y., Boukerche, A., 2020. A novel lane departure warning system for improving road safety. In: 2020 IEEE International Conference on Communications (ICC), Dublin, 2020.

Chen, M., Jochem, T., Pomerleau, D., 1995. AURORA: a vision-based roadway departure warning system. In: IEEE/RSJ International Conference on Intelligent Robots and Systems–Human Robot Interaction and Cooperative Robots, Pittsburgh, 1995.

Chiu, K.Y., Lin, S.F., 2005. Lane detection using color-based segmentation. In: Intelligent Vehicles Symposium, Las Vegas, 2005.

Choi, Y., Park, J.H., Jung, H.Y., 2018. Lane detection using labeling based RANSAC algorithm. International Journal of Computer and Information Engineering 12 (4), 245–248.

Deng, G., Wu, Y., 2018. Double lane line edge detection method based on constraint conditions Hough transform. In: IEEE 17th International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES), Wuxi, 2018.

Denton, T., 2019. Automated Driving and Driver Assistance Systems, first ed. Routledge, Abingdon.

Deusch, H., Wiest, J., Reuter, S., et al., 2012. A random finite set approach to multiple lane detection. In: 15th International IEEE Conference on Intelligent Transportation Systems, Anchorage, 2012.

Dong, Y., 2004. A review of lane departure warning highway system. Journal of Changchun Institute of Optics and Fine Mechanics 27 (1), 48–50.

Du, X., Tan, K.K., 2016. Vision-based approach towards lane line detection and vehicle localization. Machine Vision and Applications 27 (2), 175–191.

Efrat, N., Bluvstein, M., Garnett, N., et al., 2020. Semi-local 3D lane detection and uncertainty estimation. arXiv, 2003.05257.

Fan, B., 2018. Research on Monocular Vision Detection Method of Structured Road Lane Line (Master thesis). Hunan University, Changsha.

Gackslatter, C., Heinemann, P., Thoams, S., et al., 2010. Stable road lane model based on clothoids. Advanced Microsystems for Automatic Applications 2010, 133–143.

Gaikwad, V., Lokhande, S., 2015. Lane departure identification for advanced driver assistance. IEEE Transactions on Intelligent Transportation Systems 16 (2), 910–918.

Garnett, N., Cohen, R., Pe'er, T., et al., 2019. 3D-LaneNet: end-to-end 3D multiple lane detection. In: IEEE/CVF International Conference on Computer Vision (ICCV), Seoul, 2019.

Gonzalez, J.P., Ozguner, U., 2000. Lane detection using histogram-based segmentation and decision trees. In: 2000 IEEE Intelligent Transportation Systems, Dearborn, 2000.

Gopalan, R., Hong, T., Shneier, M., et al., 2012. A learning approach towards detection and tracking of lane markings. IEEE Transactions on Intelligent Transportation Systems 13 (3), 1088–1098.

Guo, Y., Chen, G., Zhao, P., et al., 2020. Gen-LaneNet: a Generalized and Scalable Approach for 3D Lane Detection. arXiv, 2003.10656.

Gupta, A., Merchant, P.S.N., 2016. Automated lane detection by k-means clustering: a machine learning approach. Electronic Imaging 2016 (14), 1–6.

He, K., Sun, J., Tang, X., 2009. Single image haze removal using dark channel prior. IEEE Transactions on Pattern Analysis and Machine Intelligence 33 (12), 2341–2353.

Hillel, A.B., Lerner, R., Levi, D., et al., 2014. Recent progress in road and lane detection: a survey. Machine Vision and Applications 25, 727–745.

Hoel, C.J., Wolff, K., Laine, L., 2018. Automated speed and lane change decision making using deep reinforcement learning. In: 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, 2018.

Hu, J., Xiong, S., Sun, Y., et al., 2020. Research on lane detection based on global search of dynamic region of interest (DROI). Applied Sciences 10 (7), 2543.

Hur, J., Kang, S.N., Seo, S.W., 2013. Multi-lane detection in urban driving environments using conditional random fields. In: 2013 IEEE Intelligent Vehicles Symposium, Gold Coast, 2013.

Huval, B., Wang, T., Tandon, S., et al., 2015. An empirical evaluation of deep learning on highway driving. arXiv, 150401716.

Jiang, R., Klette, R., Vaudrey, T., et al., 2011. Lane detection and tracking using a new lane model and distance transform. Machine Vision and Applications 22 (4), 721–737.

Jin, H., Wu, L., Chen, H., et al., 2007. An improved algorithm for the lane recognition of structured road. Transactions of Beijing Institute of Technology 27 (6), 501–505.

Joshy, N., Jose, D., 2014. Improved detection and tracking of lane marking using Hough transform. International Journal of Computer Science and Mobile Computing 3 (8), 507–513.

Jung, C.R., Kelber, C.R., 2005. Lane following and lane departure using a linear parabolic model. Image Vision Computing 23 (13), 1192–1202.

Jung, H., Min, J., Kim, J., 2013. An efficient lane detection algorithm for lane departure detection. In: 2013 IEEE Intelligent Vehicles Symposium, Gold Coast, 2013.

Jung, S., Youn, J., Sull, S., 2015. Efficient lane detection based on spatiotemporal images. IEEE Transactions on Intelligent Transportation Systems 17 (1), 289–295.

Kim, J., Baek, J., Choi, H., et al., 2016. Wet area and puddle detection for Advanced Driver Assistance Systems (ADAS) using a stereo camera. International Journal of Control, Automation and Systems 14, 263–271.
Kim, Z.W., 2008. Robust lane detection and tracking in challenging scenarios. IEEE Transactions on Intelligent Transportation Systems 9 (1), 16–26.
Kim, J., Lee, M., 2014. Robust lane detection based on convolutional neural network and random sample consensus. In: International Conference on Neural Information Processing, Kuching, 2014.
Kim, J., Park, C., 2017. End-to-end ego lane estimation based on sequential transfer learning for self-driving cars. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, Honolulu, 2017.
Ko, Y., Jun, J., Ko, D., et al., 2020. Key points estimation and point instance segmentation approach for lane detection. arXiv, 2002.06604.
Kortli, Y., Marzougui, M., Bouallegue, B., et al., 2017. A novel illumination-invariant lane detection system. In: 2nd International Conference on Anti-cybercrime (ICACC), Abha, 2017.
Küçükmanisa, A., Tarım, G., Urhan, O., 2019. Real-time illumination and shadow invariant lane detection on mobile platform. Journal of Real-time Image Processing 16, 1781–1794.
Lee, J.W., 2002. A machine vision system for lane-departure detection. Computer Vision and Image Understanding 86 (1), 52–78.
Lee, S., Kim, J., Yoon, J.S., et al., 2017. VPGNet: vanishing point guided network for lane and road marking detection and recognition. In: IEEE International Conference on Computer Vision, Venice, 2017.
Li, H., 2020. Lane Line Detection and Tracking Method Based on DeepLab-LatNet Network and Density Clustering (Master thesis). Chang'an University, Xi'an.
Li, P., 2015. Intelligent Vehicle Lane Yaw Warning Research and Development of Measurement and Control Platform (PhD thesis). Xi'an University of Technology, Xi'an.
Li, Q., 2018. Research on Lane Detection Technology of Lane Departure Warning (PhD thesis). Chengdu University of Technology, Chengdu.
Li, Y., Chen, L., Huang, H., et al., 2016. Nighttime lane markings recognition based on Canny detection and Hough transform. In: IEEE International Conference on Real-Time Computing and Robotics, Angkor Wat, 2016.
Li, J., Mei, X., Prokhorov, D., et al., 2017. Deep neural network for structural prediction and lane detection in traffic scene. IEEE Transactions on Neural Networks and Learning Systems 28 (3), 690–703.
Liang, M., 2017. Research on Key Technologies of Visual Perception of Intelligent Vehicle Driving Environment (PhD thesis). Chang'an University, Xi'an.
Liang, D., Guo, Y., Zhang, S., et al., 2020. Lane detection: a survey with new results. Journal of Computer Science and Technology 35 (3), 493–505.
Lin, Q., Han, Y., Hahn, H., 2010. Real-time lane departure detection based on extended edge-linking algorithm. In: Second International Conference on Computer Research and Development, Kuala Lumpur, 2010.
Liu, G., 2014. Research on Lane Detection and Tracking Algorithm Based on Image (PhD thesis). Hunan University, Changsha.
Liu, F., Zhang, S., Zhu, W., et al., 2010. A vision based lane detection and tracking algorithm. Journal of Tongji University (Natural Science Edition) 38 (2), 223–229, 306.
Loose, H., Franke, U., Stiller, C., 2009. Kalman particle filter for lane recognition on rural roads. In: IEEE Intelligent Vehicles Symposium, Xi'an, 2009.
López, A., Serrat, J., Canero, C., et al., 2010. Robust lane markings detection and road geometry computation. International Journal of Automotive Technology 11 (3), 395–407.
Long, J., Shelhamer, E., Darrell, T., 2015. Fully convolutional networks for semantic segmentation. In: IEEE Conference on Computer Vision and Pattern Recognition, Boston, 2015.
Lu, M., Cai, Z., Li, Y., 2010. Lane line detection method for road area segmentation. CAAI Transactions on Intelligent Systems 5 (6), 505–509.
Luo, H., Cai, J., Zhang, K., et al., 2020. A multi-task deep learning model for short-term taxi demand forecasting considering spatiotemporal dependences. Journal of Traffic and Transportation Engineering (English Edition), https://doi.org/10.1016/j.jtte.2019.07.002.
Ma, B., Lakshmanan, S., Hero, A.O., 2000. Simultaneous detection of lane and pavement boundaries using model-based multisensor fusion. IEEE Transactions on Intelligent Transportation Systems 1 (3), 135–147.
Ma, H., Ma, Y., Jiao, J., et al., 2018. Multiple lane detection algorithm based on optimised dense disparity map estimation. In: IEEE International Conference on Imaging Systems and Techniques, Krakow, 2018.
Madrid, N., Hurtik, P., 2016. Lane departure warning for mobile devices based on a fuzzy representation of images. Fuzzy Sets and Systems 291, 144–159.
Mirchevska, B., Pek, C., Werling, M., et al., 2018. High-level decision making for safe and reasonable autonomous lane changing using reinforcement learning. In: 21st International Conference on Intelligent Transportation Systems, Maui, 2018.
Mukadam, M., Cosgun, A., Nakhaei, A., et al., 2017. Tactical decision making for lane changing with deep reinforcement learning. In: 5th International Conference on Learning Representations (ICLR), Toulon, 2017.
Narote, S.P., Bhujbal, P.N., Narote, A.S., et al., 2018. A review of recent advances in lane detection and departure warning system. Pattern Recognition 73, 216–234.
Navarro, J., Deniel, J., Yousfi, E., et al., 2017. Influence of lane departure warnings onset and reliability on car drivers'. behaviors. Applied Ergonomics 59 (A), 123–131.
Navarro, J., Deniel, J., Yousfi, E., et al., 2019. Does false and missed lane departure warnings impact driving performances differently? International Journal of Human-Computer Interaction 35 (14), 1292–1302.
Neven, D., Brabandere, B.D., Georgoulis, S., et al., 2018. Towards end-to-end lane detection: an instance segmentation approach. In: IEEE Intelligent Vehicles Symposium, Changshu, 2018.
Niu, J., Lu, J., Xu, M., et al., 2015. Robust lane detection using two-stage feature extraction with curve fitting. Pattern Recognition 59, 225–233.
Obradovic, Đ., Konjović, Z., Pap, E., et al., 2013. Linear fuzzy space based road lane model and detection. Knowledge-based Systems 38, 37–47.
Ozgunalp, U., Fan, R., Ai, X., et al., 2017. Multiple lane detection algorithm based on novel dense vanishing point estimation. IEEE Transactions on Intelligent Transportation Systems 18 (3), 621–632.
Pan, X., Shi, J., Luo, P., et al., 2018. Spatial as deep: spatial CNN for traffic scene understanding. arXiv, 1712.06080.
Park, Y.K., Park, J.K., On, H.I., et al., 2015. Convolutional neural network-based system for vehicle front-side detection.

Journal of Institute of Control, Robotics and Systems 21 (11), 1008–1016.
Paszke, A., Chaurasia, A., Kim, S., et al., 2016. ENet: a deep neural network architecture for real-time semantic segmentation. arXiv, 1606.02147.
Pizzati, F., Allodi, M., Barrera, A., et al., 2019. Lane Detection and classification using cascaded CNNs. arXiv, 1907.01294.
Riener, A., 2010. Sensor-actuator Supported Implicit Interaction in Driver Assistance Systems. Vieweg+Teubner Verlag, Wiesbaden.
Romera, E., Álvarez, J.M., Bergasa, L.M., et al., 2018. ERFNet: efficient residual factorized ConvNet for real-time semantic segmentation. IEEE Transactions on Intelligent Transportation Systems 19 (1), 263–272.
Sheu, J.S., Chu, H., Liu, C.C., 2013. Implementation of lane departure warning system based on machine vision. Applied Mechanics and Materials 284–287, 2075–2079.
Shin, B.S., Tao, J., Klette, R., 2015. A super particle filter for lane detection. Pattern Recognition 48 (11), 3333–3345.
Shin, B.S., Xu, Z., Klette, R., 2014. Visual lane analysis and higher-order tasks: a concise review. Machine Vision and Applications 25 (6), 1519–1547.
Shirke, S., Udayakumar, R., 2019. Lane datasets for lane detection. In: International Conference on Communication and Signal Processing (ICCSP), Kuala Lumpur, 2019.
Sivaraman, S., Trivedi, M.M., 2013. Looking at vehicles on the road: a survey of vision-based vehicle detection, tracking, and behavior analysis. IEEE Transactions on Intelligent Transportation Systems 14 (4), 1773–1795.
Smirnov, E.A., Timoshenko, D.M., Andrianov, S.N., 2014. Comparison of regularization methods for ImageNet classification with deep convolutional neural networks. AASRI Procedia 6, 89–94.
Son, J., Yoo, H., Kim, S., et al., 2014. Real-time illumination invariant lane detection for lane departure warning system. Expert Systems with Applications 42 (4), 1816–1824.
Sternlund, S., 2017. The safety potential of lane departure warning systems—a descriptive real-world study of fatal lane departure passenger car crashes in Sweden. Traffic Injury Prevention 18 (sup1), 518–523.
Sun, L., Wu, Q., Zhao, J., et al., 2018. Empirical study on influencing factors of traffic accidents in China from 2004 to 2015. Journal of Southwest University (Natural Science Edition) 40 (11), 118–124.
Tan, H., Zhou, Y., Zhu, Y., et al., 2014. A novel curve lane detection based on improved river flow and RANSA. In: 17th International IEEE Conference on Intelligent Transportation Systems (ITSC), Qingdao, 2014.
Teng, Z., Kim, J.H., Kang, D.J., 2010. Real-time lane detection by using multiple cues. In: ICCAS 2010, Gyeonggi-Do, 2010.
Tsai, C.C., Lin, C.Y., Guo, J.I., 2019. Dark channel prior based video dehazing algorithm with sky preservation and its embedded system realization for ADAS applications. Optics Express 27 (9), 11877–11901.
Tseng, D.C., Lin, C.W., 2013. Versatile lane departure warning using 3D visual geometry. International Journal of Innovative Computing, Information and Control 9 (5), 1899–1917.
Wang, X., 2017. Lane Line Recognition of Structured Road Based on Monocular Vision and Lane Departure Detection Based on SAE Algorithm (PhD thesis). Shandong University, Jinan.
Wang, W., Chen, W., Wang, K., et al., 2020. Extraction of tunnel centerline and cross sections on fractional calculus, 3D invariant moments and best-fit ellipse. Optics & Laser Technology 128, 106220.
Wang, Q., Gao, J., Yuan, Y., 2017. Embedding structured contour and location prior in siamesed fully convolutional networks for road detection. IEEE Transactions on Intelligent Transportation Systems 19 (1), 230–241.
Wang, W., Li, H., Wang, K., et al., 2020. Pavement crack detection on geodesic shadow removal with local oriented filter on LOF and improved Level set. Construction and Building Materials 237, 117750.
Wang, W., Li, R., Wang, K., et al., 2020. Crack and fracture central line delineation on Steger and hydrodynamics with improved fractional differential. International Journal of Wavelets, Multiresolution and Information Processing 18 (5), 2050037.
Wang, B., Qi, Z., Ma, G., 2014. Robust lane recognition for structured road based on monocular vision. Journal of Beijing Institute of Technology 23 (3), 345–351.
Wang, W., Wang, M., Li, H., et al., 2019. Pavement crack image acquisition methods and crack extraction algorithms: a review. Journal of Traffic and Transportation Engineering (English edition) 6 (6), 535–556.
Wang, J., Wu, Y., Liang, Z., et al., 2010. Lane detection based on random Hough transform on region of interesting. In: The 2010 IEEE International Conference on Information and Automation, Harbin, 2010.
Wang, W., Zhao, D., Han, W., et al., 2018. A learning-based approach for lane departure warning systems with a personalized driver model. IEEE Transactions on Vehicular Technology 67 (10), 9145–9157.
Wei, X., Zhang, Z., Chai, Z., et al., 2018. Research on lane detection and tracking algorithm based on improved hough transform. In: IEEE International Conference of Intelligent Robotic and Control Engineering (IRCE), Lanzhou, 2018.
Word Health Organization (WHO), 2019. Global Status Report on Road Safety 2018. WHO, Geneva.
Wu, P.C., Chang, C.Y., Lin, C.H., 2014. Lane-mark extraction for automobiles under complex conditions. Pattern Recognition 47 (8), 2756–2767.
Xiao, J., Luo, L., Yao, Y., et al., 2020. Lane detection based on road module and extended Kalman filter. In: Pacific-rim Symposium on Image and Video Technology, Sydney, 2019.
Xing, Y., Lv, C., Wang, H., et al., 2020. An ensemble deep learning approach for driver lane change intention inference. Transportation Research Part C: Emerging Technologies 115, 102615.
Xu, X., Chen, Q., Cai, Y., et al., 2020. Real-time lane departure warning based on fusion segmentation and LASSO regression. Journal of Wuhan University of Science and Technology 43 (1), 50–58.
Ye, F., Wu, G., Boriboonsomsin, K., et al., 2018. Development and evaluation of lane hazard prediction application for connected and automated vehicles (CAVs). In: 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, 2018.
Yenikaya, S., Yenikaya, G., Düven, E., 2013. Keeping the vehicle on the road: a survey on on-road lane detection systems. ACM Computing Surveys 46 (1), 2.
Yi, S.C., Chen, Y.C., Chang, C.H., 2015. A lane detection approach based on intelligent vision. Computers & Electrical Engineering 42, 23–29.
Yoo, H., Yang, U., Sohn, K., 2013. Gradient-enhancing conversion for illumination-robust lane detection. IEEE Transactions on Intelligent Transportation Systems 14 (3), 1083–1094.
You, F., Zhang, R., Lie, G., et al., 2015. Trajectory planning and tracking control for autonomous lane change maneuver based on the cooperative vehicle infrastructure system. Expert Systems with Applications 42 (14), 5932–5946.
Yu, H., 2017. Research on the Development Strategy of CSJ Company (Master thesis). South China University of Technology, Guangzhou.
Yu, Z., Wu, X., Shen, L., 2017. Illumination invariant lane detection algorithm based on dynamic region of interest. Computer Engineering 43 (2), 43–47, 56.

Yu, B., Zhang, W., Gong, Z., 2009. Lane departure warning system based on machine vision. Journal of Southeast University (Natural Science Edition) 39 (5), 928–932.
Yuan, Y., Jiang, Z., Wang, Q., 2015. Video-based road detection via online structural learning. Neurocomputing 168, 336–347.
Zhang, T., 2017. Research on Complex Background Lane Line Detection Based on Fractional Theory and Least Square Method (Master thesis). Chang'an University, Xi'an.
Zhang, Z., Hao, X., Liu, S., et al., 2016. Line detection based on Hough one-dimensional transform. Acta Optica Sinica 36 (4), 166–173.
Zheng, F., Luo, S., Song, K., et al., 2018. Improved lane line detection algorithm based on Hough transform. Pattern Recognition and Image Analysis 28 (2), 254–260.
Zhang, Z., Ma, X., 2019. Lane recognition algorithm using the Hough transform based on complicated conditions. Journal of Computer and Communications 7 (11), 65–75.
Zhang, J., Zhou, P., Zhang, Q., 2018. Low-light image enhancement based on iterative multi-scale guided filter retinex. Journal of Graphics 39 (1), 1–11.
Zhou, T., 2016. Research and Test of Lane Line Detection and Tracking Algorithm Based on Monocular Vision (Master thesis). Central China Normal University, Wuhan.
Zhou, S., Jiang, Y., Xi, J., et al., 2010. A novel lane detection based on geometrical model and Gabor filter. In: IEEE Intelligent Vehicles Symposium, San Diego, 2010.
Zou, Q., Jiang, H., Dai, Q., et al., 2020. Robust lane detection from continuous driving scenes using deep neural networks. IEEE Transactions on Vehicular Technology 69 (1), 41–54.

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