Lane Detection and Tracking

Subjects: Transportation Science & Technology
Contributor: Nirajan Shiwakoti

Lane detection and tracking are the advanced key features of the advanced driver assistance system. Lane detection is the process of detecting white lines on the roads. Lane tracking is the process of assisting the vehicle to remain in the desired path, and it controls the motion model by using previously detected lane markers.

Keywords: lane detection ; lane tracking system ; lane departure warning system ; advanced driver assistance system ; automated vehicles

1. Introduction

Autonomous passenger vehicles are a direct implementation of transportation-related autonomous robotics research. They are also known as self-driving vehicles or driverless vehicles. Shakey the robot (1966–1972) is the first autonomous mobile robot that has been documented [1]. It was developed by Stanford Research Institute's Artificial Intelligence Centre and was capable of detecting the environment, thinking, planning, and navigation. In basic settings, vision-based lane tracking and obstacle avoidance sparked interest in autonomous vehicles [2]. In the early 1990s, The Royal Armament Research and Development Establishment in the United Kingdom created two vehicles for obstacle-free navigation on and off the road [3]. In the United States, the first operations of autonomous driving in realistic settings dates back to Carnegie Mellon University's NavLab in the early 1990s [4]. The vehicle developed by NavLab was operated at very low speeds due to the limited computational power available at the time. Early US research projects also included the California PATH project, which developed the automated highway [5]. Vehicle steering was automated with manual longitudinal control in the "No Hands Across America" project [6]. In early 2000, CyberCars, one of several European projects began developing technologies based on automated transport [7]. The announcement of the defence advanced research projects agency (DARPA) grand challenge in 2003 generated research interest in autonomous cars. Following that, in 2006, the DARPA urban challenge was performed in a controlled situation with a variety of autonomous and human-operated vehicles. Since then, many manufactures, including Audi, BMW, Bosch, Ford, GM, Lexus, Mercedes, Nissan, Tesla, Volkswagen, Volvo and Google, have launched self-driving vehicle projects in collaboration with universities [8]. Google's self-driving car has experimented and travelled 500 thousand kilometres and has begun building prototypes of its own cars [9]. A completely autonomous vehicle would be expected to drive to a chosen location without any expectation of shared control with the driver, including safety-critical tasks.

The performance of lane detection and tracking depends on the well-developed roads and their lane markings, so smart cities are also a prominent factor in autonomous vehicle research. The idea of a smart city is often linked with an eco-city or a sustainable city, both of which seek to enhance the quality of municipal services while lowering their costs. Smart cities' primary goal is to balance technological innovation with the economic, social, and environmental problems that tomorrow's cities face. The greater closeness between government and people is required in smart cities that embrace the circular economy's concepts [10]. The way materials and goods flow around people and their demands will alter, as will the structure of cities. Several car manufacturers such as Tesla and Audi have already launched autonomous vehicle marketing for private use. Soon, society will be influenced by autonomous vehicles' spread to urban transport systems [11]. The development of smart cities with the introduction of connected and autonomous vehicles could potentially transform cities and guide long-term urban planning [10].

Autonomous vehicles and Advanced Driver Assistance Systems (ADAS) are predicted to provide a higher degree of safety and reduce fuel and energy consumption and road traffic emissions. ADAS is implemented for safe and efficient driving, which has many driver assistance features such as warning drivers about forwarding collision warning or safe lane change [12]. Research shows that most accidents occur because of driver errors, and the ADAS can reduce the accidents and workload of the driver. If there is a likelihood of an accident, ADAS can take the necessary action to avoid it [13]. Lane departure warning (LDW), which utilizes lane detection and tracking algorithms, is an essential feature of the ADAS. The LDW warns the driver when a vehicle crosses white lane lines unintentionally and controls the vehicle by bringing it back into the desired safe path. Three types of approaches for lane detection are usually discussed in the existing literature: learning-based approach, features-based approach, and model-based approach [13][14][15][16][17][18] . Many challenges and issues have been highlighted in the literature regarding the LDW systems, such as visibility conditions change, variation in images, and lane appearance diversity [17]. Since different countries have used various lane markers, there is a challenge for lane detection and tracking to solve the problems.

2. Lane Detection and Tracking Algorithms

The feature-based approach uses edges and local visual characteristics of interest, such as gradient, colour, brightness, texture, orientation, and variations, which are relatively insensitive to road shapes but sensitive to illumination effects. The model-based approaches apply global road models to fit low levels of features that are more robust against illumination effects, but they are sensitive to road shapes [13][14]. The geometrics parameters are used in the model-based approach for lane detection [16][17][18]. The learning-based approach consists of two stages: training and classification. The training process uses previously known errors and system properties to construct a model, e.g., program variables. In addition, the classification phase applies the training model to the user set of properties and outputs that are more likely to be correlated with the error ordered by their probability of fault discloser [19]. It is then followed up by summary tables (**Table 1**, **Table 2**, **Table 3** and **Table 4**) that present the key features of these algorithms and strengths, weaknesses, and future prospects.

Table 1. A summary of methods used for lane detection and tracking with general remarks.

Methods	Steps	Tool Used	Data Used	Methods Classification	Remarks
Image and sensor-based lane detection and tracking	• Image frames are pre-processed • Lane detection algorithm is applied • The sensors values are used to track the lanes	• Camera • Sensors	**sensors values**	**Feature-based approach**	**Frequent calibration is required for accurate decision making in a complex environment**
Predictive controller for lane detection and controller	**Machine learning technique (e.g., neural networks,)**	• Model predictive controller • Reinforcement learning algorithms	**data obtained from the controller**	**Learning-based approach**	**Reinforcement learning with model predictive controller could be a better choice to avoid false lane detection.**
Robust lane detection and tracking	• Capture an image through camera • Use Edge detector to data for extract the features of the image • Determination of vanishing point	**Based on robust lane detection model algorithms**	**Real-time**	**Model-based approach**	**Provides better result in different environmental conditions. Camera quality plays important role in determining lanes marking**

Table 2. A comprehensive summary of lane detection and tracking algorithm.

Sources	Data		Method Used	Advantages	Drawbacks	Results	Tool Used	Future Prospects	Data	Reason for Drawbacks
	Simulation	Real								
[20]		Y	Inverse perspective mapping method is applied to convert the image to bird's eye view.	Minimal error and quick detection of lane.	The algorithm performance drops when driving in tunnel due to the fluctuation in the lighting conditions.	The lane detection error is 5%. The cross-track error is 25% and lane detection time is 11 ms.	Fisheye dashcam, inertial measurement unit and ARM processor-based computer.	Enhancing the algorithm suitable for complex road scenario and with less light conditions.	Data obtained by using a model car running at a speed of 100 m/s.	Performance drop in determining the lane, if the vehicle is driving in a tunnel and the road conditions where there is no proper lighting. The complex environment creates unnecessary tilt causing some inaccuracy in lane detection.
[21]		Y	Kinematic motion model to determine the lane with minimal parameters of the vehicle.	No need for parameterization of the vehicle with variables like cornering stiffness and inertia. Prediction of lane even in absence of camera input for around 3 s.	The algorithm suitable for different environment situation not been considered	Lateral error of 0.15 m in the absence of camera image.	Mobileye camera, carsim and MATLAB/Simulink, Auto box from dSPACE.	Trying the fault tolerant model in real vehicle.	Test vehicle	----
[22]	Y		Usage of inverse mapping for the creation of bird's eye view of the environment.	Improved accuracy of lane detection in the range of 86%to 96% for different road types.	Performance under different vehicle speed and inclement weather conditions not considered.	The algorithm requires 0.8 s to process frame. Higher accuracy when more than 59% of lane markers are visible.	Firewire color camera, MATLAB	Real-time implementation of the work	Highway and streets and around Atlanta	----
[23]	Y	Y	Hough transform to extract the line segments, usage of a convolutional neural network-based classifier to determine the confidence of line segment.	Tolerant to noise	In the custom dataset, the performance drops compared to Caltech dataset.	For urban scenario, the proposed algorithm provides accuracy greater than 95%. The accuracy obtained in lane detection in the custom setup is 72% to 86%.	OV10650 camera and I MU is Epson G320.	Performance improvement is future consideration.	Caltech dataset and custom dataset.	The device specification and calibration, it plays important role in capturing the lane.

Sources	Data		Method Used	Advantages	Drawbacks	Results	Tool Used	Future Prospects	Data	Reason for Drawbacks
	Simulation	Real								
[24]		Y	Feature-line-pairs (FLP) along with Kalman filter for road detection.	Faster detection of lanes, suitable for real-time environment.	Testing the algorithm suitability under different environmental conditions could be done.	Around 4 ms to detect the edge pixels, 80 ms to detect all the FLPs, 1 ms to determine the extract road model with Kalman filter tracking.	C++; camera and a matrox meteor RGB/ PPB digitizer.	Robust tracking and improve the performance in urban dense traffic.	Test robot.	------
[25]	Y		Dual thresholding algorithm for pre-processing and the edge is detected by single direction gradient operator. Usage of the noise filter to remove the noise.	The lane detection algorithm insensitive headlight, rear light, cars, road contour signs.	The algorithm detects the straight lanes during the night.	Detection Of straight lanes.	Camera with RGB channel.	-------	Custom dataset	Suitability of the algorithm for different types of roads during night to be studied.
[26]	Y		Determination of region of interest and conversion of binary image via adaptive threshold.	Better accuracy	The algorithm needs changes for checking its suitability for the day time lane detection	90% accuracy during night at isolated highways	Firewire S400 camera and MATLAB	Geometrics transformation of image for increasing the accuracy and intensity normalization.	Custom dataset	The constraints and assumption considered do not suit for the day time.
[27]	Y		Canny edge detector algorithm is used to detect the edges of the lanes.	Hough transform improves the output of the lane tracker.	------	Performance of the proposed system is better.	Raspberry pi based robust with camera and sensors.	Simulation of the proposed method by using raspberry Pi based robot with a monocular camera and radar-based sensors to determine the distance between neighboring vehicles.	Custom data	------
[28]	Y		Video processing technique to determine the lanes illumination change on the region of interest.	----	----	Robust performance	vision-based vehicle	Determine the lanes illumination changes on the region of interest for curve line roads	Simulator	----
[29]	Y	Y	A colour-based lane detection and representative line extraction algorithm is used.	Better accuracy in the day time.	Algorithm needs changes to test in different scenario.	The results show that the lane detection rate is more than 93%.	MATLAB	There is scope to test the algorithm in the night time.	Custom data	Unwanted noise reduces the performance of the algorithm.

Sources	Data: Simulation	Data: Real	Method Used	Advantages	Drawbacks	Results	Tool Used	Future Prospects	Data	Reason for Drawbacks
[30]		Y	Proposed hardware architecture for detecting straight lane lines using Hough transform.	Proposed algorithm provides better accuracy for occlusion, poor line paintings.	Computer complexity and high cost of HT (Hough transform)	Algorithm tested under various conditions of roads such as urban street, highway and algorithm provides a detection rate of 92%.	Virtex-5 ML 505 platform	Algorithm need to test with different weather condition.	Custom	-----
[31]		Y	Proposed a lane detection methodology in a circular arc or parabolic based geometric method.	Video sensor improves the performance of the lane marking.	Performance dropped in lane detection when entering the tunnel region	Experiment performed with different road scene and provided better results.	maps, video sensors, GPS.	Proposed method can test with previously available data.	Custom	Due to low illumination
[32]	Y		Proposed a hierarchical lane detection system to detect the lanes on the structured and unstructured roads.	Quick detection of lanes.	----	The system achieves an accuracy of 97% in lane detection.	MATLAB	----		----
[33]		Y	LIDAR sensor-based boundary detection and tracking method for structured and unstructured roads.	Regardless of road types, algorithm detect accurate lane boundaries.	Urban driving scenario for unstructured roads since it perceives the arbitrary road shape	The road boundary detection accuracy is 95% for structured roads and 92% for unstructured roads.	Test vehicle with LIDAR, GPS and IMU.	Algorithm needs to test with RADAR based and vision-based sensors.	Custom data	IMU sensors could be incorporated to avoid the arbitrary road shape
[34]	Y		Proposed a method to detect the pedestrian lanes under different illumination conditions with no lane markings.	Robust performance for pedestrian lane detection under unstructured environment.	More challenging for indoor and outdoor environment.	The result shows that the lane detection accuracy is 95%.	MATLAB	There is scope for structured roads with different speeds limit	New dataset of 2000 images (custom)	Complex environment
[35]	Y	Y	The proposed system is implemented using an improved Hough transform which pre-process different light intensity road images and convert it to the polar angle constraint area.	Robust performance for a campus road, in which the road does not have lane markings.	Performance drops due to low intensity of light	----	Test vehicle and MATLAB	-------	Custom data	Low illumination

Table 3. A comprehensive summary of learning-based model predictive controller lane detection and tracking.

Sources	Data: Simulation	Data: Real	Method	Advantages	Drawbacks	Result	Tool Used	Future Prospects	Data	Reason for Drawback
[38]		Y	Gradient cue, color cue and line clustering are used to verify the lane markings.	The proposed method works better under different weather conditions such as rainy and snowy environments.	The suitability of the algorithm for multi-lane detection of lane curvature is to be studied.	Except rainy condition during the day, the proposed system provides better results.	C++ and OpenCV on ubuntu operating system. Hardware: duel ARM cortex-A9 processors.	Algorithm can test on an isolated highway, urban roads.	48 video clips from USA and Korea	Since the road environment may not be predictable, leads to false detection.
[39]	Y		Extraction of lanes from the captured image, Random sample consensus algorithm is used to eradicate error in lane detection.	Multilane detection even during poor lane markings. No prior knowledge about the lane is required.	Difficult to track lane boundaries quality has to be improved in cardova 2dataset because of low contract, curb of the sidewalk as a lane.	The Caltech lane datasets consisting of four types of urban driving scenarios: Cordova 1; Cordova 2; Washington2; with a total of 1224 frames containing 4172 lane markings.	MATLAB	Real time implementation of the proposed algorithm	Data from South Korea road and Caltech dataset.	Low contract false detection of lanes.
[40]	Y	Y	Rectangular detection region is formed on the image. Edge points of lane is extracted using threshold algorithm. A modified Brenham line voting space is used to detect lane segment.	Robust lane detection method by using a monocular camera in which the roads are provided with proper lane markings.	Performance drops when road is not flat	In Cardova 2 dataset, the false detection value is higher around 38%. The algorithm shows better performance under different roads geometries such as straight, curve, polyline and complex	Software based performance analysis on Caltech dataset for different urban driving scenario. Hardware implementation on the Tuyou autonomous vehicle.	----	Caltech and custom-made dataset	Due to the difficulty In image capturing false detection happened. More training or inclusion of sensors for live dataset collection will help to mitigate it.

Sources	Data: Simulation	Data: Real	Method	Advantages	Drawbacks	Result	Tool Used	Future Prospects	Data	Reason for Drawback
[36]	Y		A lane detection algorithm based on camera and 2D LIDAR input data.	Computational and experimental results show the method significantly increases accuracy.	------	The proposed approach shows better accuracy compared with the traditional methods for distance less than 9 m.	software based analysis and MATLAB	Proposed method need to test with RADAR and vision-based sensors data	Fusion of camera and 2D LIDAR data	-----
[41]		Y	Based on voting map, detected vanishing points, usage of distinct property of lane colour to obtain illumination invariant lane marker and finally found main lane by using clustering methods.	Overall method test algorithm within 33 ms per frame.	Need to reduce computational complexity by using vanishing point and adaptive ROI for every frame.	Under various illumination condition lane detection rate of the algorithm is an average 93%.	Software based analysis done.	There are chances, to test algorithm at day time with inclement weather conditions.	Custom data based on Real-time	-----
[37]	Y		A deep learning-based approach for detecting lanes, object and free space.	The Nvidia tool comes with SDK (software development kit) with inbuild options for object detection, lane detection and free space.	Monocular camera with advance driver assistance system is costly.	The time taken to determine the lane falls under 6 to 9 ms.	C++ and NVidia's drive PX2 platform	Complex road scenario with different high intensity of light.	KITT	----
[42]	Y		Proposed a sharp curve lane from the input image based on hyperbola fitting. The input image is converted to grayscale image and the feature namely left edge, right edge and the extreme points of the lanes are calculated	Better accuracy for sharp curve lanes.	The suitability of the algorithm for different road geometrics yet to study.	The results show that the accuracy of lane detection is around 97% and the average time taken to detect the lane is 20 ms.	Custom made simulator C/C++ and visual studio	-----	Custom data	-----

Table 4. A comprehensive summary of robust lane detection and tracking.

Sources	Data: Simulation	Data: Real	Method Used	Advantages	Drawbacks	Result	Tool Used	Future Prospects	Data	Reason for Drawbacks
[43]	Y		vanishing point detection method for unstructured roads	Accurate and robust performance for unstructured roads.	Difficult to obtain robust vanishing point for detection of lane for unstructured scene.	The accuracy of vanishing point range between 80.9% to 93.6% for different scenarios.	Unmanned ground vehicle and mobile robot.	Future scope for structured roads with different scenarios.	Custom data	Complex background interference and unclear road marking.
[45]		Y	Inverse perspective mapping method is applied to convert the image to bird's eye view.	Quick detection of lane.	The algorithm performance drops due to the fluctuation in the lighting conditions.	The lane detection error is 5%. The cross-track error is 25% lane detection time is 11 ms.	Fisheye dashcam: inertial measurement unit; Arm processor-based computer.	Enhancing the algorithm suitable for complex road scenario and with less light conditions.	Data obtained by using a model car running at a speed of 1 m/s	The complex environment creates unnecessary tilt causing some inaccuracy in lane detection.
[44]	Y		Proposed a lane detection approach using Gaussian distribution random sample consensus (G-RANSAC), usage of rider detector to extract the features of lane points and adaptable neural network for remove noise.	Provides better results during the presence of vehicle shadow and minimal illumination of the environment.	---	The proposed algorithm is tested under different illumination condition ranging from normal, intense, normal and poor and provides lane detection accuracy as 95%, 92%, 91% and 90%.	Software based analysis	Need to test proposed method under various times like day, night.	Test vehicle	----
[46]	Y		Deep learning-based reinforcement learning is used for decision making in the changeover. The reward for decision making is based on the parameters like traffic efficiency	Cooperative decision-making processes involving the reward function comparing delay of a vehicle and traffic.	Validation expected to check the accuracy of the lane changing algorithm for heterogeneous environment	The performance is fine-tuned based on the cooperation for both accident and non-accidental scenario.	Custom made simulator	Dynamic selection of cooperation coefficient under different traffic scenario	Newell car following model.	----

Sources	Data: Simulation	Data: Real	Method Used	Advantages	Drawbacks	Result	Tool Used	Future Prospects	Data	Reason for Drawbacks
[47]	Y		Reinforcement learning-based approach for decision making by using Q-function approximator.	Decision-making process involving reward function comprising yaw rate, yaw acceleration and lane changing time.	Need for more testing to check the efficiency of the approximator function for its suitability under different real-time conditions.	The reward functions are used to learn the lane in a better way.	Custom made simulator	To test the efficiency of the proposed approach under different road geometrics and traffic conditions. Testing the feasibility of the reinforcement learning with fuzzy logic for image input and controller action based on the current situation.	custom	More parameters could be considered for the reward function.
[48]	Y		Probabilistic and prediction for the complex driving scenario.	Usage of deterministic and probabilistic prediction of traffic of other vehicles to improve the robustness	Analysis of the efficiency of the system under real-time noise is challenging.	Robust decision making compared to the deterministic method. Lesser probability of collision.	MATLAB/Simulink and carsim. Used real-time setup as following: Hyundai-Kia motors K7, mobile eye camera system, micro auto box II, Delphi radars, IBEO laser scanner.	Testing undue different scenario	Custom dataset (collection of data using test vehicle).	The algorithm to be modified for real [illegible] for real-time monitoring.
[49]	Y		Usage of pixel hierarchy to the occurrence of lane markings. Detection of the lane markings using a boosting algorithm. Tracking of lanes using a particle filter.	Detection of the lane without prior knowledge on road model and vehicle speed.	Usage of vehicles inertial sensors GPS information and geometry model further improve performance under different environmental conditions.	Improved performance by using support vector machines and artificial neural networks on the image.	Machine with 4-GHz processor capable of working on image approximately 240 × 320 image at 15 frames per second.	To test the efficiency of the algorithm by using the Kalman filter.	custom data	Calibration of the sensors needs to be maintained.

Some of the key observations from **Table 3**, **Table 4** and **Table 5** are summarized below:

- Frequent calibration is required for accurate decision making in a complex environment.
- Reinforcement learning with the model predictive control could be a better choice to avoid false lane detection.
- Model-based approaches (robust lane detection and tracking) provide better results in different environmental conditions. Camera quality plays an important role in determining lane marking.
- The algorithm’s performance depends on the type of filter used, and the Kalman filter is mostly used for lane tracking.
- In a vision-based system, image smoothing is the initial lane detection and tracking stage, which plays a vital role in increasing systems performance.
- External disturbances like weather conditions, vision quality, shadow and blazing, and internal disturbances such as too narrow, too wide, and unclear lane marking, drop algorithm performance.
- The majority of researchers (>90%) have used custom datasets for research.
- Monocular, stereo and infrared cameras have been used to capture images and videos. The algorithm’s accuracy depends on the type of camera used, and a stereo camera gives better performance than a monocular camera.
- The lane markers can be occluded by a nearby vehicle while doing overtake.
- There is an abrupt change in illumination as the vehicle gets out of a tunnel. Sudden changes in illumination affect the image quality and drop the system performance.
- The results show that the lane detection and tracking efficiency rate under dry and light rain conditions is near 99% in most scenarios. However, the efficiency of lane marking detection is significantly affected by heavy rain conditions.
- It has been seen that the performance of the system drops due to unclear and degraded lane markings.
- IMU (Inertia measurement unit) and GPS are examples that help to improve RADAR and LIDAR’s performance of distance measurement.
- One of the biggest problems with today’s ADAS is that changes in environmental and weather conditions have a major effect on the system’s performance.

References

1. Nilsson, N.J. Shakey the Robot; Sri International Menlo Park: California, CA, USA, 1984.
2. Tsugawa, S.; Yatabe, T.; Hirose, T.; Matsumoto, S. An Automobile with Artificial Intelligence. In Proceedings of the 6th International Joint Conference on Artificial Intelligence, Tokyo, Japan, 20 August 1979.
3. Blackman, C.P. The ROVA and MARDI projects. In Proceedings of the IEEE Colloquium on Advanced Robotic Initiatives in the UK, London, UK, 17 April 1991; pp. 5/1–5/3.

4. Thorpe, C.; Herbert, M.; Kanade, T.; Shafter, S. Toward autonomous driving: The CMU Navlab. II. Architecture and systems. IEEE Expert. 1991, 6, 44–52.
5. Horowitz, R.; Varaiya, P. Control design of an automated highway system. Proc. IEEE 2000, 88, 913–925.
6. Pomerleau, D.A.; Jochem, T. Rapidly Adapting Machine Vision for Automated Vehicle Steering. IEEE Expert. 1996, 11, 19–27.
7. Parent, M. Advanced Urban Transport: Automation Is on the Way. Intell. Syst. IEEE 2007, 22, 9–11.
8. Lari, A.Z.; Douma, F.; Onyiah, I. Self-Driving Vehicles and Policy Implications: Current Status of Autonomous Vehicle Development and Minnesota Policy Implications. Minn. J. Law Sci. Technol. 2015, 16, 735.
9. Urmson, C. Green Lights for Our Self-Driving Vehicle Prototypes. Available online: https://blog.google/alphabet/self-driving-vehicle-prototypes-on-road/ (accessed on 30 September 2021).
10. Campisi, T.; Severino, A.; Al-Rashid, M.A.; Pau, G. The Development of the Smart Cities in the Connected and Autonomous Vehicles (CAVs) Era: From Mobility Patterns to Scaling in Cities. Infrastructures 2021, 6, 100.
11. Severino, A.; Curto, S.; Barberi, S.; Arena, F.; Pau, G. Autonomous Vehicles: An Analysis both on Their Distinctiveness and the Potential Impact on Urban Transport Systems. Appl. Sci. 2021, 11, 3604.
12. Aly, M. Real time Detection of Lane Markers in Urban Streets. In Proceedings of the 2008 IEEE Intelligent Vehicles Symposium, Eindhoven, The Netherlands, 4–6 June 2008; pp. 7–12.
13. Bar Hillel, A.; Lerner, R.; Levi, D.; Raz, G. Recent progress in road and lane detection: A survey. Mach. Vis. Appl. 2014, 25, 727–745.
14. Ying, Z.; Li, G.; Zang, X.; Wang, R.; Wang, W. A Novel Shadow-Free Feature Extractor for Real-Time Road Detection. In Proceedings of the 24th ACM International Conference on Multimedia, Amsterdam, The Netherlands, 15–19 October 2016.
15. Jothilashimi, S.; Gudivada, V. Machine Learning Based Approach. 2016. Available online: https://www.sciencedirect.com/topics/computer-science/machine-learning-based-approach (accessed on 20 August 2021).
16. Zhou, S.; Jiang, Y.; Xi, J.; Gong, J.; Xiong, G.; Chen, H. A novel lane detection based on geometrical model and Gabor filter. In Proceedings of the 2010 IEEE Intelligent Vehicles Symposium, La Jolla, CA, USA, 21–24 June 2010; pp. 59–64.
17. Zhao, H.; Teng, Z.; Kim, H.; Kang, D. Annealed Particle Filter Algorithm Used for Lane Detection and Tracking. J. Autom. Control Eng. 2013, 1, 31–35.
18. Paula, M.B.; Jung, C.R. Real-Time Detection and Classification of Road Lane Markings. In Proceedings of the 2013 XXVI Conference on Graphics, Patterns and Images, Arequipa, Peru, 5–8 August 2013.
19. Kukkala, V.K.; Tunnell, J.; Pasricha, S.; Bradley, T. Advanced Driver-Assistance Systems: A Path toward Autonomous Vehicles. In IEEE Consumer Electronics Magazine; IEEE: Eindhoven, The Netherlands, 2018; Volume 7, pp. 18–25.
20. Kuo, C.Y.; Lu, Y.R.; Yang, S.M. On the Image Sensor Processing for Lane Detection and Control in Vehicle Lane Keeping Systems. Sensors 2019, 19, 1665.
21. Kang, C.M.; Lee, S.H.; Kee, S.C.; Chung, C.C. Kinematics-based Fault-tolerant Techniques: Lane Prediction for an Autonomous Lane Keeping System. Int. J. Control Autom. Syst. 2018, 16, 1293–1302.
22. Borkar, A.; Hayes, M.; Smith, M.T. Robust lane detection and tracking with ransac and Kalman filter. In Proceedings of the 2009 16th IEEE International Conference on Image Processing (ICIP), Cairo, Egypt, 7–10 November 2009; pp. 3261–3264.
23. Sun, Y.; Li, J.; Sun, Z. Multi-Stage Hough Space Calculation for Lane Markings Detection via IMU and Vision Fusion. Sensors 2019, 19, 2305.
24. Lu, J.; Ming Yang, M.; Wang, H.; Zhang, B. Vision-based real-time road detection in urban traffic, Proc. SPIE 4666. In Real-Time Imaging VI; SPIE: Bellingham, WA, USA, 2002.
25. Zhang, X.; Shi, Z. Study on lane boundary detection in night scene. In Proceedings of the 2009 IEEE Intelligent Vehicles Symposium, Xi’an, China, 3–5 June 2009; pp. 538–541.
26. Borkar, A.; Hayes, M.; Smith, M.T.; Pankanti, S. A layered approach to robust lane detection at night. In Proceedings of the 2009 IEEE Workshop on Computational Intelligence in Vehicles and Vehicular Systems, Nashville, TN, USA, 30 March–2 April 2009; pp. 51–57.
27. Priyadharshini, P.; Niketha, P.; Saantha Lakshmi, K.; Sharmila, S.; Divya, R. Advances in Vision based Lane Detection Algorithm Based on Reliable Lane Markings. In Proceedings of the 2019 5th International Conference on Advanced

Computing & Communication Systems (ICACCS), Coimbatore, India, 15–16 March 2019; pp. 880–885.

28. Hong, G.-S.; Kim, B.-G.; Dorra, D.P.; Roy, P.P. A Survey of Real-time Road Detection Techniques Using Visual Color Sensor. J. Multimed. Inf. Syst. 2018, 5, 9–14.
29. Park, H. Implementation of Lane Detection Algorithm for Self-driving Vehicles Using Tensor Flow. In International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing; Springer: Cham, Switzerland, 2018; pp. 438–447.
30. El Hajjouji, I.; Mars, S.; Asrih, Z.; Mourabit, A.E. A novel FPGA implementation of Hough Transform for straight lane detection. Eng. Sci. Technol. Int. J. 2020, 23, 274–280.
31. Samadzadegan, F.; Sarafraz, A.; Tabibi, M. Automatic Lane Detection in Image Sequences for Vision-based Navigation Purposes. ISPRS Image Eng. Vis. Metrol. 2006. Available online: https://www.semanticscholar.org/paper/Automatic-Lane-Detection-in-Image-Sequences-for-Samadzadegan-Sarafraz/55f0683190eb6cb21bf52c5f64b443c6437b38ea (accessed on 12 August 2021).
32. Cheng, H.-Y.; Yu, C.-C.; Tseng, C.-C.; Fan, K.-C.; Hwang, J.-N.; Jeng, B.-S. Environment classification and hierarchical lane detection for structured and unstructured roads. Comput. Vis. IET 2010, 4, 37–49.
33. Han, J.; Kim, D.; Lee, M.; Sunwoo, M. Road boundary detection and tracking for structured and unstructured roads using a 2D lidar sensor. Int. J. Automot. Technol. 2014, 15, 611–623.
34. Le, M.C.; Phung, S.L.; Bouzerdoum, A. Lane Detection in Unstructured Environments for Autonomous Navigation Systems. In Asian Conference on Computer Vision; Cremers, D., Reid, I., Saito, H., Yang, M.H., Eds.; Springer: Cham, Switzerland, 2015.
35. Wang, J.; Ma, H.; Zhang, X.; Liu, X. Detection of Lane Lines on Both Sides of Road Based on Monocular Camera. In Proceedings of the 2018 IEEE International Conference on Mechatronics and Automation (ICMA), Changchun, China, 5–8 August 2018; pp. 1134–1139.
36. YenIaydin, Y.; Schmidt, K.W. Sensor Fusion of a Camera and 2D LIDAR for Lane Detection. In Proceedings of the 2019 27th Signal Processing and Communications Applications Conference (SIU), Sivas, Turkey, 24–26 April 2019; pp. 1–4.
37. Kemsaram, N.; Das, A.; Dubbelman, G. An Integrated Framework for Autonomous Driving: Object Detection, Lane Detection, and Free Space Detection. In Proceedings of the 2019 Third World Conference on Smart Trends in Systems Security and Sustainablity (WorldS4), London, UK, 30–31 July 2019; pp. 260–265.
38. Lee, C.; Moon, J.-H. Robust Lane Detection and Tracking for Real-Time Applications. IEEE Trans. Intell. Transp. Syst. 2018, 19, 1–6.
39. Son, Y.; Lee, E.S.; Kum, D. Robust multi-lane detection and tracking using adaptive threshold and lane classification. Mach. Vis. Appl. 2018, 30, 111–124.
40. Li, Q.; Zhou, J.; Li, B.; Guo, Y.; Xiao, J. Robust Lane-Detection Method for Low-Speed Environments. Sensors 2018, 18, 4274.
41. Son, J.; Yoo, H.; Kim, S.; Sohn, K. Real-time illumination invariant lane detection for lane departure warning system. Expert Syst. Appl. 2014, 42.
42. Chae, H.; Jeong, Y.; Kim, S.; Lee, H.; Park, J.; Yi, K. Design and Vehicle Implementation of Autonomous Lane Change Algorithm based on Probabilistic Prediction. In Proceedings of the 2018 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, HI, USA, 4–7 November 2018; pp. 2845–2852.
43. Chen, P.R.; Lo, S.Y.; Hang, H.M.; Chan, S.W.; Lin, J.J. Efficient Road Lane Marking Detection with Deep Learning. In Proceedings of the 2018 IEEE 23rd International Conference on Digital Signal Processing (DSP), Shanghai, China, 19–21 November 2018; pp. 1–5.
44. Lu, Z.; Xu, Y.; Shan, X. A lane detection method based on the ridge detector and regional G-RANSAC. Sensors 2019, 19, 4028.
45. Bian, Y.; Ding, J.; Hu, M.; Xu, Q.; Wang, J.; Li, K. An Advanced Lane-Keeping Assistance System with Switchable Assistance Modes. IEEE Trans. Intell. Transp. Syst. 2019, 21, 385–396.
46. Wang, G.; Hu, J.; Li, Z.; Li, L. Cooperative Lane Changing via Deep Reinforcement Learning. arXiv 2019, arXiv:1906.08662.
47. Wang, P.; Chan, C.Y.; de La Fortelle, A. A reinforcement learning based approach for automated lane change maneuvers. In Proceedings of the 2018 IEEE Intelligent Vehicles Symposium (IV), Changshu, China, 26–30 June 2018; pp. 1379–1384.
48. Suh, J.; Chae, H.; Yi, K. Stochastic model-predictive control for lane change decision of automated driving vehicles. IEEE Trans. Veh. Technol. 2018, 67, 4771–4782.

49. Gopalan, R.; Hong, T.; Shneier, M.; Chellappa, R. A learning approach towards detection and tracking of lane markings. IEEE Trans. Intell. Transp. Syst. 2012, 13, 1088–1098.