

CURRENT APPROACHES IN TRAFFIC LANE DETECTION: A MINIREVIEW

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Abstract

The continuous development and importance of the field of road transport these days make it necessary to design, develop and implement technological solutions that reduce (eliminate as much as possible) the risk of road accidents. Such a technological solution is also represented by advanced driver assistance systems (ADAS), systems that assist drivers in various ways, such as collision avoidance, automatic parking, adaptive cruise control, attention and lane departure warnings. Over the next ten years, there will likely be a rise in the need for ADAS system deployment in automobile construction, driven by consumer and regulatory interest in safety applications that protect drivers and lower accident rates. At the moment, autonomous emergency braking and forward collision warning systems are mandated for all cars in the US and the EU. Additionally, advanced driver assistance systems (ADAS) may soon distinguish automobile brands and have a significant impact on consumer preference. The present work aims to provide a general picture related to the current research and development of ADAS systems that refer to the detection of the traffic lane and lane markings. The approaches are presented regarding: the current development directions of ADAS systems, current traffic lane detection techniques, traffic lane detection methods and the use of artificial intelligence techniques in this field. The general conclusion is that further research is needed in the field, to increase the performance of traffic lane detective systems by using advanced algorithms and easy-to-implement methods that do not require large hardware resources.

Keywords: ADAS; autonomous driving technology; traffic lane detection; algorithm; artificial intelligence

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1. Introduction

It is a contemporary certainty that mobility due to the use of means of transport is strongly correlated with social and individual well-being and contributes greatly and directly to increasing the quality of life. The field of transportation is a very important and necessary part of trade and services, therefore it can be said to be the basis of a nation's economy, in this sense, for example, industrialized countries have achieved a high degree of mobility through the existence of mass production of motor vehicles and concurrent with infrastructure development. However, human civilization has to pay a price for the short-term benefits of mobility. Apart from the maintenance expenses that come with owning and operating a vehicle, fuel, and infrastructure, mass mobility also involves extra economic, ecological, and social costs associated with resource consumption, air and noise pollution, road congestion, accidents, and lost productivity due to these factors [1]. An ambitious goal at the level of the European Union is the one defined by the Vision Zero concept of massive reduction of accidents caused by road traffic, which through various programs and strategies aims to reduce by 50%, until 2030, the number of deceased people and the number of people seriously injured because of road accidents (compared to 2019).

Thus, it can be considered that through the last generation technologies used in the construction of vehicles, the current and future means of transport are and will be so designed and made that safety (active and passive) represents an important parameter. An attempt is made to combine appropriate safety measures, taking into account all relevant aspects of their effect and the development process of a vehicle, making every effort to maintain a reasonable price for the final product. A new chapter in the development (history) of automobiles has begun with the introduction and deployment of advanced driver assistance systems (ADAS), which have allowed for a reduction in road traffic-related fatalities. By utilizing modern technology that are accessible to automakers and engineers, significant advancements in road safety have been realized [2].

Due to the complexity of the technologies used, there is no exact definition of ADAS systems, but a general description provided by Gietelink [3] can be accepted, namely that the ADAS system *"is a vehicle control system that uses sensors to improve driving, comfort and/or traffic safety by assisting the driver in recognizing and reacting to potentially dangerous traffic situations"*. Currently, the vehicles put into circulation and which are equipped with ADAS systems, have systems that are classified at the levels of complexity between 0 and 2 (level 2 is defined as "partial automation" – Figure 1) that help the driver in taking decisions but without replacing him in the process of driving the vehicle. Initially, there were developed and implemented different concepts of systems that assist the driver through independent intervention. Since the first electronic anti-lock braking system (ABS) was launched in 1978, these systems have been referred to as driver aid systems (DAS). Development continued with the introduction and implementation of the electronic stability control system (ESC) and the traction control system (TCS) in the functional construction of the vehicle (Figure 1). The functions of DAS are

relatively simple being characterized by only two types of systemic parameters entering the system: the state of the vehicle and the intention of the driver. With the use of sensors that can detect objects outside the vehicle (such as other cars, pedestrians, and other roadblocks), ADAS systems and their complexity allow for the introduction of the external environment's condition as a new kind of input system parameter. The complexity of the vehicle rises with the addition of more sensors, which has an immediate impact on the processes involved in system testing and verification. When it comes to testing and verification, the primary parallels between ADAS and DAS functions occur in the last stages of development, when both kinds of systems are installed in actual cars and driven on public roads. Thus arises the great challenge of using these technologies to increase road safety, because ADAS functions use input parameters from the vehicle's external environment, which must be taken into account to recreate different types of scenarios that can be encountered in traffic.

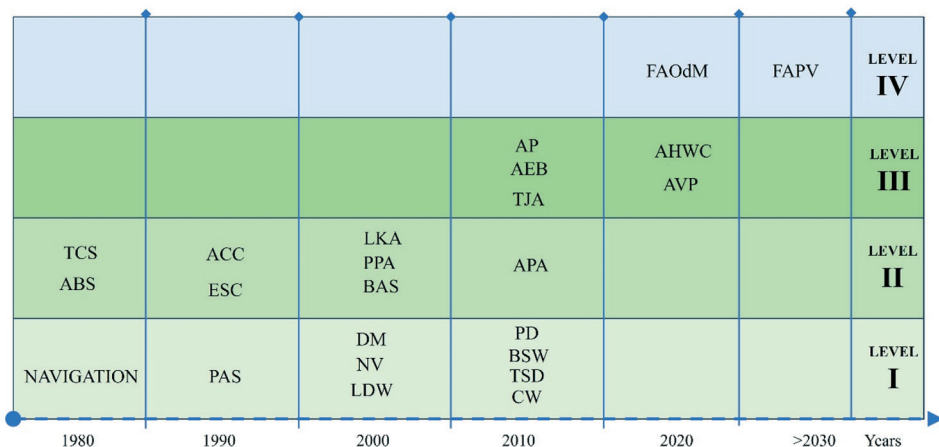


Fig. 1. Chronological development and level of complexity (I to IV) of driver assistance systems [adapted from [4]]

Therefore, for a primary validation of the concept, it is necessary that the first stages of the development of ADAS functions be based on computer simulation processes, the costs required for real tests being high and not providing the necessary feasibility for the development process of a motor vehicle [4]. Another aspect that requires the use of simulations as a technology for the development of ADAS systems is the existence of scenarios in real test conditions that present immediate dangers and risks to other traffic participants. Autonomous Emergency Braking (AEB) and Lane Keeping Assist (LKA) systems, for instance, have the potential to cause serious property damage if they are tested in traffic, in addition to putting the driver and other drivers in danger. This is one of the reasons why any developed ADAS system needs to be tested in all possible scenarios in a virtual environment and only after this step to be verified on public roads.

From the point of view of increasing the safety of motor vehicle operation, many things have been achieved in terms of improving the safety of vehicle occupants and other road users, through legislation and through organizations such as Euro NCAP, which, according to the report PIN ETSC, have helped save more than 78,000 lives [5]. The increase in road safety is also related to political direction. The European Commission presents several directives, including the "Europe on the Move" plan, to improve road safety through technological innovation and automation [6]. The ultimate goal is to halve road accidents in Europe in the coming years and the existence of these emerging technologies has led to the fact that the institutions and regulatory bodies in the automotive field take them into account. Thus, Euro NCAP included several ADAS systems considered in the testing process, such as: emergency braking, speed control systems, lane keeping and road sign detection systems [7].

2. Directions for Development of ADAS Systems

The direction of development and implementation of ADAS systems in new vehicles is to create increasingly complex and integrated ADAS functions. In addition, ADAS systems are being studied that do not strictly refer to the immediate environment of the vehicle but are capable of establishing a V2X type of communication (V2I infrastructure vehicle communication or V2V vehicle communication) which is constantly growing. Finally, in the future, there will be fully autonomous vehicles for which the autonomous driving system will be able to replace the driver in all traffic situations (level 5). Arguably, the immediate future for ADAS systems means the development of levels 3 and 4 autonomous driving, which include systems such as Autopilot on Highway (AHC), Autopilot in Traffic Jam (TJA) and Automated Valet Parking (AVP). These systems require the cooperation of several already developed systems such as automatic braking and distance maintenance, but their continuous development is necessary to work in all possible conditions.

The main purpose of ADAS systems is to help and assist the driver while driving and therefore prevent accidents from occurring. This is achieved through the prediction abilities of ADAS systems on the possibilities/risks of road accidents in combination with warning the driver and/or taking control of the vehicle. Road safety is a social problem in the world, in Europe alone, more than 40,000 victims and 1.4 million injuries are caused by motor vehicle accidents every year [8]. Traffic accident statistics show that more than 90% of traffic accidents are caused by driver mistakes, such as improper behavior, distraction and fatigue [9]. Although the continued development and implementation of passive safety technologies (Figure 2) has contributed to the manufacture of increasingly safer vehicles, it has been found that the potential to further improve passive safety is limited [10]. Active safety systems such as ABS and ESP [11] offer possibilities to improve traffic safety by assisting the driver while driving, especially in emergency situations.

Advanced driver assistance systems (ADAS) have the potential to significantly reduce the number of road accidents, and the technological solutions already applied are multiple, such as Adaptive Cruise Control (ACC), Intelligent Speed Adaptation (ISA) or warning systems against collisions (CWS). The simplest advanced assistance systems provide different types of information and warning systems to adaptive functions that provide longitudinal control of the vehicle by accelerating or braking in different traffic conditions and/or lateral control by steering system command [12, 13].

Monitoring and correcting driver intent while driving is critical to the effectiveness of ADAS systems. Smart vehicles can be equipped with multiple high-resolution sensors to monitor traffic around the vehicle if the car can predict the driver's purpose, the system will pay closer attention to the intended maneuver and assess the likelihood of such a maneuver based on the surrounding traffic. Thus, estimating the driver's intention prior to the maneuver helps improve traffic safety. Meanwhile, the rising usage of in-car infotainment systems and other devices (such as mobile phones) might distract the driver. It is possible that the driver does not check the surrounding traffic situation carefully enough before executing a maneuver.

For the design of high-performance ADAS systems, it is necessary to understand the driver's intentions and the system to correctly execute intervention actions [14, 15]. However, the use of these systems does not depend only on the performance of the system, and it can be stated that nowadays these assistance systems are not able to help the driver in all driving situations in traffic. By construction and functionality these systems are based on a multi-modal system represented by the fusion of several sensors (lidar, radar, camera and GPS) in a single system.

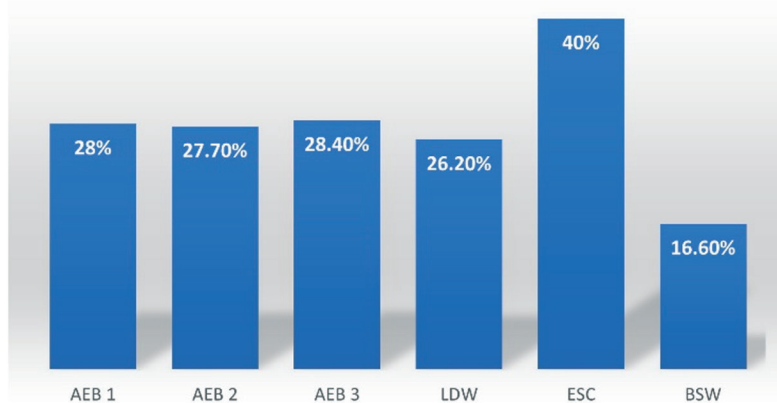


Fig. 2. Accidents reduction rate using ADAS systems: AEB 1- intersection accidents, AEB 2 – rear end accidents, AEB 3 – against pedestrian accidents, LDW – lane departure accidents, ESC – skidding and overturning accidents, BSW – lane change accidents (adapted from [10])

It should be noted that ADAS functions have several limitations that directly depend on traffic, weather and road conditions. For example, low visibility on the road can disable ADAS systems that use the video camera as an input parameter, while the absence of lane markings on the roadside can interrupt the operation of the lane keeping system (LKA). ADAS systems are becoming more complex regarding the constructive aspects of these systems (sensors, hardware part and software part) and are becoming more and more widespread in the automotive industry. Therefore, an efficient design and evaluation methodology for such systems is necessary both from the point of view of increasing their performance and because the number of active accident-avoidance systems is growing rapidly in the automotive industry, which requires the establishment of methodologies of design, development and testing that consumes as little time and resources [human and material] as possible.

3. Current traffic lane detection techniques

A large number of statistical data show that traffic accidents caused by leaving the traffic lane represent 50% of the total number of traffic accidents [16] and from this point of view the development of safety systems must solve several problems related to: road detection, lane marking detection, vehicle detection and collision avoidance [17]. The detection of the traffic lane on which the vehicle is traveling is an important decision and creates difficulties, because in real situations, it is not enough to detect only the traffic or objects in the current lane, the perception tasks related to the detection of all road markings being necessary for the entire field of view [18]. Drivers subconsciously intuit the traffic situation or road conditions, thus preparing themselves for dangerous road conditions such as dangerous turns, obstacles on the road, the behavior of other road users, etc. That is why lane detection is also a fundamental process in autonomous driving, because if the prediction concerns the moving trajectories of the vehicle [19] or detects the vehicles in front [20, 21], the marker detection tapes can always act as an additional aid in making the best decisions. In addition to autonomous driving, landmark detection also contributes to robot navigation [22] and provides information necessary for the movement of visually impaired people [23].

Lane recognition is still a challenging task, though, due to the complex scenarios that arise in real-world traffic: unsigned or interrupted lanes, abrupt curves, fluctuating visibility due to varying weather conditions, etc. The two major key characteristics of lane detection systems are resilience and accuracy. Vision-based detection is particularly common as most highways have defined lanes and camera equipment is inexpensive [24]. The primary perceptual markers for humans are lane markings, road borders, and road color and texture. In order to slow down and adjust the vehicle's path to the surroundings, autonomous cars typically utilize an optical or video camera in conjunction with GNSS (global positioning satellite system) and LiDAR (or RADAR) technologies. It should not be forgotten that autonomous vehicles must share the roads with human drivers, and therefore these vehicles must perceive the environment and adapt to different traffic situations in a similar way as a human. Creating a reliable

detection system that functions in all traffic and environmental scenarios is still a challenge. [there are too many variables, such as traffic density, traffic complexity, fog, rain, solar brightness variation, etc.].

Most algorithms based on image acquisition and processing for traffic lane detection use the following methodology [see Figure 3]:

- Aerial perspective image transformation (bird's eye view): This perspective transformation is useful (using HT – Hough transformation algorithm for e.g.) for removing perspective distortion from the image created by the video camera (although disturbances due to camera position and road flatness can significantly influence the image transformation process) [25, 26].
- Lane Marking Feature Extraction: It is needed to identify only the pixels that belong to the lane line markings. Methods to achieve this and presented in the literature include adaptive and global image delineation methods (e.g. adaptive Canny), filters, edge detection [25, 27].
- Model fitting: It is the process of converting the traffic lane into a mathematical representation, using linear and parabolic models. Obviously these models are approximations of the real lines but they have the advantage of being efficient in terms of the required computing power and memory. Real lines are better described by higher degree polynomial curves and splines. Rural and urban roads can contain various discontinuities, which require continuous, more sophisticated and detailed modeling [28].
- Time integration methods: usually applied to use previous information in the process of identifying marks/traffic lanes on the current image. Most of the approaches in the current literature are stochastic in nature, using Kalman and particle filters. It has been found that Kalman filters tend to perform well for roads with visible markings [29].

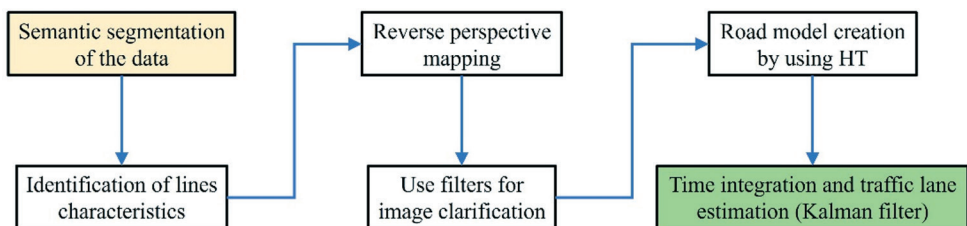


Fig. 3. General steps of traffic lane detection based on image processing methods [adapted from [25]]

4. Traffic lane detection approaches and methods

4.1. Introduction

Due to the requirement for the system to be able to recognize lane boundaries from the processed image and manage the vehicle to follow the road ahead, lane detection is a crucial stage in the development and use of autonomous driving systems. Before the vehicle responds, the algorithm must be able to calculate the lane parameters in real time and send out the necessary commands. The process of detecting traffic lines mainly uses video cameras that take snapshots of the road infrastructure. After making these video captures, the following steps are related to: preprocessing and image processing, traffic line detection and traffic line tracking. This review will present the information and elements related to the methods and algorithms used in the detection of traffic lines by analyzing the two major components of the detection process, namely: video image capture and AI modeling (Figure 4).

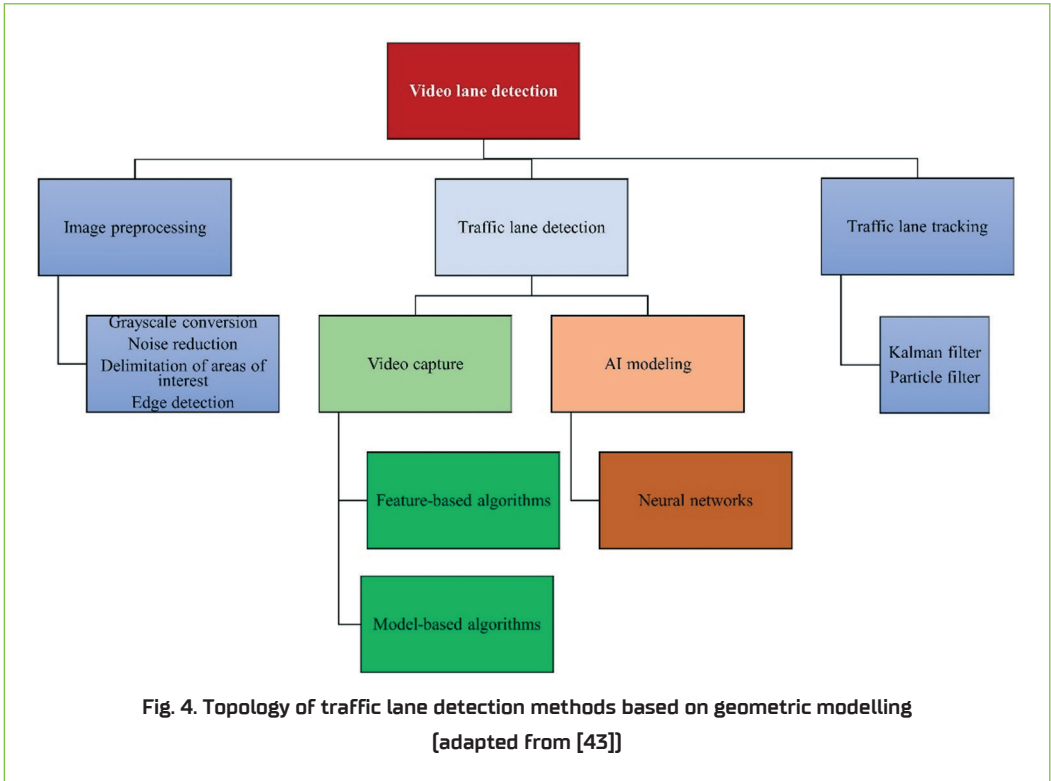


Fig. 4. Topology of traffic lane detection methods based on geometric modelling [adapted from [43]]

Vision-based traffic lane detection algorithms can be divided into two major classes of algorithms:

- Feature-based algorithms: Color, texture analysis, and lane edge recognition are the three main building blocks of feature-based algorithms [30–32]. Hough transformation (HT) and inverse perspective transform are effective feature-based algorithms for traffic lane recognition [33, 34]. These techniques can be used to reduce lane detecting mistakes and enhance noise filtering. The inverse perspective transform can be used to successfully eliminate perspective distortions from cameras and recover traffic lane features [24].
- Model-based algorithms: Since model-based algorithms generate traffic lanes from linear, parabolic, and spline curve models, they are more resilient to difficult situations. Spline patterns are widely used because they can accommodate lane markings of any shape. Wang et al.'s research [35] employed models with spline fitting, and they further enhanced these models with the B-snake model, which enhances the modeling of identified markers and traffic lanes in curves. Another model-based technique that is utilized is random sample consensus (RANSAC), which is employed because it can estimate traffic lane parameters interactively [36].

4.2. Traffic lane lines detection using feature-based algorithms

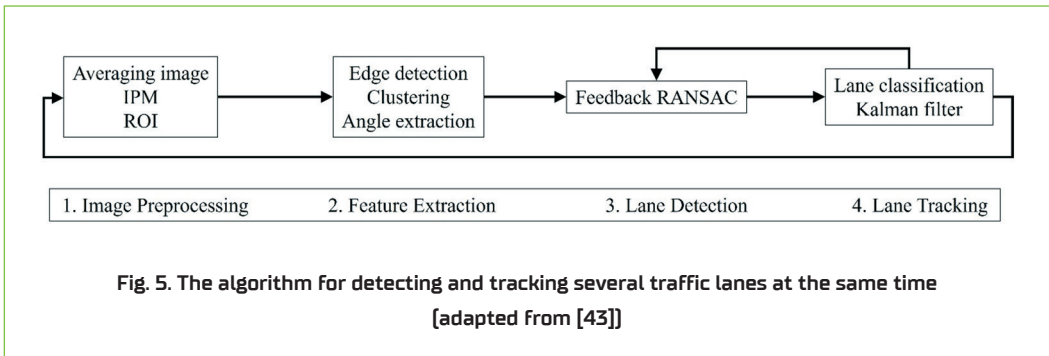
Most methods apply a two-stage solution: the first stage is edge detection and the second is matching certain types of lines to the detected lines [35–38]. Different types of filters are used for edge detection, and for e.g., traffic lane edges from bird-view images were calculated using Gaussian [28] and Gabor filters [36] and for line shape adjustment, Hough transformation (HT) models are often used [34]. The Catmull–Rom Spline model was used to construct a lane using six landmark points [39], and the B-snake method was used to describe curved lines in traffic lane detection [40]. In addition, traffic lane detection based on geometric modelling can also be implemented with stereo image analysis, where the distance of the traffic lane can be estimated/calculated [41, 42].

Son Y et al. [43] proposed a robust lane detection (and tracking) system with the main purpose of lane detection considering the surrounding environment under different atmospheric conditions, such as clear sky, rainy and snowy morning and night. The proposed detection process consists of three main phases, namely: detection initialization, traffic lane detection, and traffic lane tracking.

In the initialization phase, the road image is captured, registered and preprocessed. In the preprocessing phase, the resolution of the recorded image is reduced, the region of interest is delimited and the edges are detected. In the mark detection phase, marks are determined in the rectangular region of interest and the image is converted to grayscale. By using the line edge detection method, a line segment bounded by surrounding vehicles, shadows, trees, and buildings in the region of interest is determined. In the lane tracking phase, the process

is performed by analyzing the region of interest, with several pairs of lanes being considered. Using the procedures indicated in Figure 5, a strong multi-lane recognition and tracking algorithm (acting simultaneously) was created to recognize lanes with high accuracy under various road conditions, such as poor marking color, barriers, or guardrails [37]. An adaptive threshold is used to extract traffic lane features from images that are not sharp. The next step is to extract the erroneous traffic lane features and apply the RANSAC algorithm to prevent false lane detection. The selected traffic lanes are checked using the classification algorithm. The advantage of this approach is that it is not necessary to geometrically determine the lines that delimit the lanes. Li et al. proposed a real-time lane detection method consisting of three steps: extracting road lane markings, estimating the geometric model, and tracking points from the geometric model created in the previous step [37]. This method has a weak point that is integrated in the stage of determining the traffic lane, which is the choice of the width of the traffic lane which is directly related to the standards followed in the respective country.

Through further research, Son J et al. proposed an improved method that is fast and can determine the property traffic lane under different illumination conditions [44]. The proposed method consists of three stages. The first stage reduces the captured image to the area containing road information (with the help of the HT method and edge determination with the Canny filter). Depending on the illumination/optical reflectance property, the traffic lane markings should be either white or yellow in the following step. To obtain the binary image of the markers, utilize the white and yellow markers. The strips are named in the last stage, and points on the marks are identified so that they can be connected to each other in the next step of identifying the concrete strips (Figure 6).



Chen et al. proposed a method that combines the capability of neural networks with conventional methods for traffic lane detection [45]. The process of detecting the traffic lane consists of: generation of markings, grouping and adaptation of the geometric model for the lane (Figure 7). An artificial neural network based on encoder-decoder architecture is used to determine the markers. The traffic lane detection process involves forming a group comprising neighboring pixels represented as a single label belonging to the same marker

and connecting the labels (a process called supermarking). The next step of traffic lane model fitting uses a 3rd order polynomial to represent straight and curved traffic lanes. The major disadvantage of the method is that the method requires serious hardware resources to train the neural network.

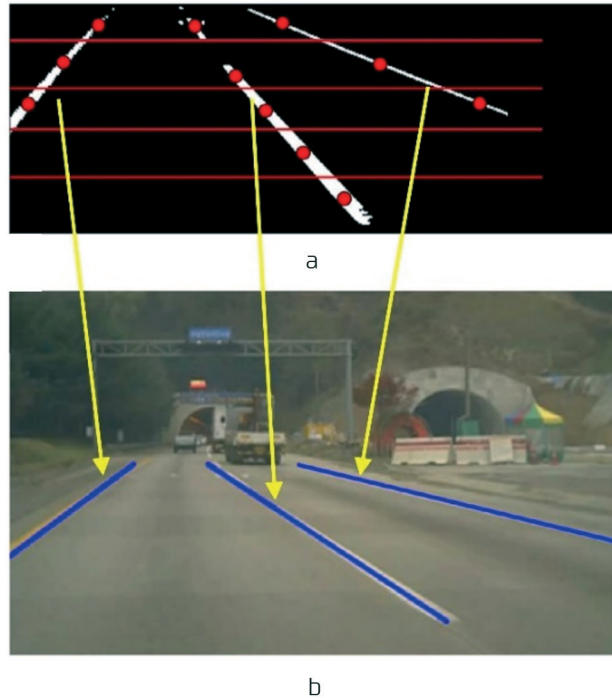


Fig. 6. Determination of reference points on markings a) and determination of markers b) by the method proposed in [44]

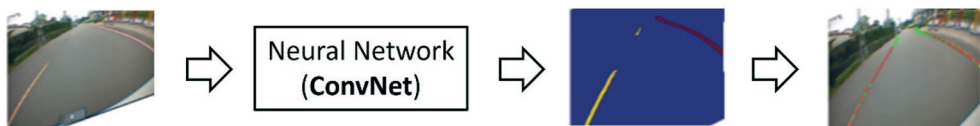


Fig. 7. Lane detection process using neural networks (ConvNet) [adapted from [45]]

A traffic lane recognition technique utilizing the Gaussian random distribution algorithm was proposed by Lu et al. [46]. In order to extract the features of the traffic lane points and remove noise, recorded photos are converted into an aerial perspective image and then a neural network is used. Grayscale-transformed photos are used to extract lane edge features, and these yield superior results when there are car shadows and dim ambient

lighting. The suggested method was tested in a variety of lighting scenarios, including good asphalt, intense lighting, typical lighting, and interrupted or damaged markings. All of these scenarios also included interference from other vehicles and poor lighting.

4.3. Feature-based traffic lane lines detection

The initial stages of traffic lane detection—image registration, identifying the image's region of interest, and preprocessing—remain similar to those of the techniques that were previously described. It differs only in the fourth stage, which has to do with extracting features from images. To recognize lane lines, image feature-based algorithms primarily use pixel gradient, color characteristics, and lane form features [47]. The image is initially converted to a grayscale image using the feature extraction method, after which data on the traffic lane region or the feature of its edge is extracted. Kang et al. proposed a system that is tolerant to errors caused by sensor operation, specifically in the absence of images provided by the camera [48]. In the absence of input data from the video camera, the vehicle trajectory is determined using data from the IMU such as vehicle accelerations and velocity. The road curvature is modelled using a cubic polynomial, and in the absence of camera images the polynomial coefficients remain stored in memory and are further used to define the traffic lane geometry. The results show that the proposed method can maintain an accepted geometric shape of the traffic lane for 3 seconds (in the absence of images captured and provided by the camera). The developed algorithm was simulated for different operating cases using CARSIM and Simulink simulation environments (Figure 8).

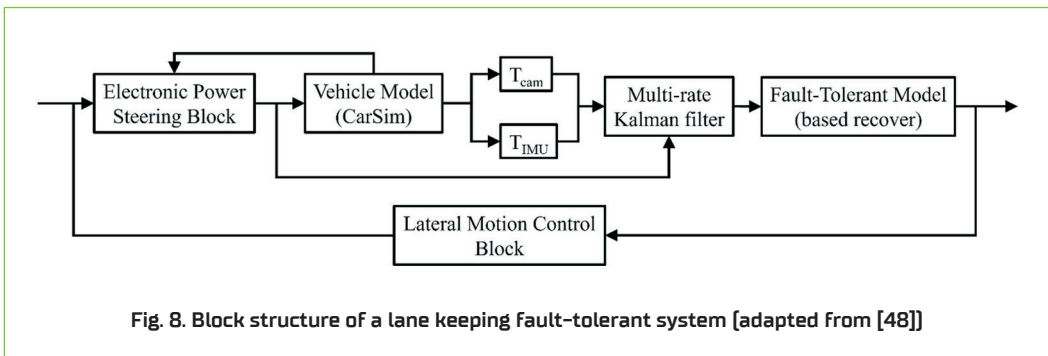


Fig. 8. Block structure of a lane keeping fault-tolerant system [adapted from [48]]

Borkar et al. proposed a lane detection and tracking method using inverse perspective image mapping (IPM) to create a top view of the road [a Hough transformation for marking detection, RANSAC algorithm for noise filtering, and Kalman filter for lane tracking] [49]. The image recorded by the video camera is converted to grayscale and then the IPM procedure is applied. Lanes are detected by identifying the pair of parallel lines that are separated by a certain distance. The transformed images are converted to binary code to which the HT is applied. Further, image is divided into two and to determine the center of the traffic lane the

one-dimensional filter is applied to each image. The Kalman filter is used to track the lane, which takes into account the lane orientation and the difference between the current and previous images. The performance of the proposed algorithm provides a very good accuracy on the highway, and on urban roads the accuracy is 86% [Figure 9].



Fig. 9. Application scenarios of the traffic lane detection method in different traffic scenarios: a) highway, b) presence of additional markings [adapted from [49]]

Through research by Sun et al., a method for lane detection based on vision and inertial measurement unit was developed [50]. Building a probabilistic Hough space from a single recorded frame and filtering the probabilistic Hough space into consecutive frames are the two primary components of the method. An effective Hough transformation and a convolutional neural network (CNN) are used to extract and categorize line segments from images, yielding the probabilistic Hough space. The filtered probabilistic Hough space is created by aligning and smoothing the line segments that make up the traffic lane using a Kalman filter and information from the IMU [Figure 10]. Fitting parabolic models to line segments with high probability values in the filtered probabilistic Hough space yields the traffic lane detection result in the end. The researchers compared the suggested approach to other approaches that were already in use and assessed the method's efficacy across a number of datasets. The obtained results showed that the method can achieve robust and accurate traffic lane detection in different scenarios [Figure 11].



Fig. 10. Determining line segments using a video camera and IMU [adapted from [50]]



Fig. 11. Examples of data sets used in traffic lane detection: a) urban traffic, b) interurban traffic, c) fog, d) night [adapted from [50]]

Park et al. proposed a color-based traffic lane detection and representative line extraction algorithm [51]. The algorithm consists of three steps: image preprocessing, lane detection and lane tracking. Image preprocessing involves converting the recorded image to grayscale, followed by binary image conversion to remove shadows, and the Canny filter is used for edge detection. Traffic lane detection involves finding lines in the image after extracting the region of interest, filtering out irrelevant lines, and grouping the remaining lines into (left and right) lane markers. Lane tracking involves using the Kalman filter to estimate lane parameters and draw boundaries on the original image. The algorithm was tested during the day, and the results showed that the detection rate of the traffic lane is higher than 93%.

El Hajjouji et al. proposed another method for detecting straight lines using the Hough transformation, which consists in simplifying the method by eliminating unnecessary detections (vertical or perfectly horizontal lines) [52]. The algorithm was tested on a variety of images with different lighting and road conditions, such as urban streets, highways, etc., yielding a 92% detection rate of straight lines. In the article published by Yeniaydin and Schmidt, a traffic lane detection algorithm based on sensor fusion between video camera and 2D LiDAR was proposed [30]. The images obtained by the camera are transformed into aerial perspective images, and the LiDAR detects the location of the objects. The proposed method consists of the steps mentioned below (Figure 12):

- Data is obtained from video cameras and 2D LiDAR;
- Data provided by LiDAR is segmented to recognize different objects based on determining the distance between points;
- Mapping objects on the aerial perspective image obtained from the video camera;
- Transform pixels from detected objects and black pixels.

In Figure 12, the LiDAR beams hit the vehicle in the area of the red dots and the detected rectangle is shown in blue and the shaded area in yellow dashed lines. Identifying the traffic lanes in the binary image by using the marker line detection method.

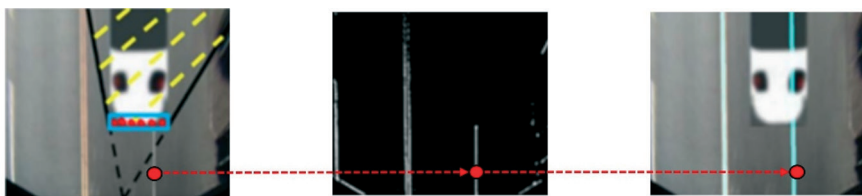


Fig. 12. Using the aerial perspective visualization process for traffic lane detection [adapted from [30]]

4.4. Traffic lane lines detection using artificial intelligence

Current artificial intelligence technologies (Machine Learning–ML and Deep Learning–DL) are used to increase the ability to detect and recognize traffic lanes. Convolutional Neural Network (CNN) possesses some unique properties such as high detection accuracy, automatic feature learning, and landmark recognition [24]. The recurrent neural network (RNN) introduced by Li et al. [37] helps to detect the traffic lane in a video sequence not only based on the captured image but also using the internal memory. RNN also helps to recognize and connect markings that are not seen due to other vehicles or other objects.

The concept of artificial intelligence (AI) holds that computer programs can imitate human thought processes, and today there are many applications of AI in the industry, ranging from speech and facial recognition to traffic sign identification. Large amounts of labeled training data are typically required by AI systems in order to identify particular correlations or patterns that will be utilized in the operation of systems that are based on them in the future. The majority of conventional lane detecting technologies exhibit inefficient behavior in complicated environments or need processing times that are too long to fulfill real-time requirements [31]. The application of AI through Deep Learning (DL) has become popular in lane detection research, a technique that uses artificial neural networks to detect and locate lane markings in camera images [38]. In general, this involves training a neural network to classify the pixels in the recorded images as belonging to a traffic lane or not, then using the results of the network to identify the location and shape of the markings. This method is sometimes more accurate and robust than traditional lane detection algorithms that rely on logic and geometric shape detection.

DL-based traffic lane detection is widely used in many applications due to the advantage of adapting to diverse environments and situations. A variety of DL methods have been applied for traffic lane detection. The methods range from early convolutional neural networks ([51, 53, 54]), segmentation-based methods (GCN [55], SCNN [56]) to GAN-based methods (EL-GAN [55]). In addition, the development of new techniques like "*knowledge distillation*"

[56], and the generation of "attention map" [57] brought innovative ideas for traffic lane detection, which involve the evolution of the algorithm without external intervention (for example, SAD [58]). Although promising results have been obtained, the lack of generalizability is still a major challenge of existing methods. A CNN trained in one scenario may perform less accurately in another scenario (especially under night-time traffic conditions). Existing approaches to detect lane marking can be one-step method and two-step method [13]. The first stage is related to the recognition and extraction of traffic lane elements with DL patterns. In contrast, the second stage refers to the application of post-processing methods, which may include geometric arrangement of markers and clustering of detected objects.

• Image preprocessing

The step of preprocessing the images captured by the video cameras is important to reduce the running time and computational power required for the analysis. ROI cropping is a technique used to eliminate unnecessary data from input (recorded) photographs. It often involves removing the sky from the image, which reduces the image complexity by 30% [59]. The input data set for CNN models can be improved by applying certain techniques shown in Figure 13.



Fig. 13. Different image preprocessing methods: a) original image, b) cropped/enlarged image, c) illuminated image [adapted from [60]]

• Using CNN for traffic lane detection

Kim and Lee first proposed a method that used a CNN model to extract traffic lane data from images and the RANSAC method to determine consecutive traffic lane positions [53]. Figure 14 depicts the architecture of the CNN model that was utilized for the investigation, consist of two subsampling layers (S), three fully connected lay convolutional layers (C). The photos in the training dataset have undergone edge detection and ROI cropping. The anticipated image (with a size of 100x15 pixels), with the projected traffic lane pixels highlighted in white, is produced by the final completely connected layer. Although this method shows improved performance compared to classical methods, it has certain limitations. It requires complex pre-processing and expensive in terms of the required computational power, but also the architecture of the CNN model is complex (8 layers), which led to the development of improved neural networks to overcome the limitations.

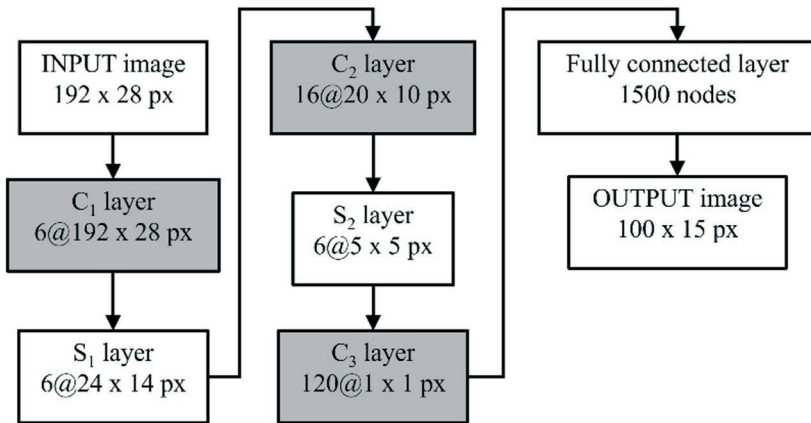


Fig. 14. CNN neural network architecture for traffic lane detection according to [53]

• **Using Deep Learning methods**

The use of DL methods in the detection of traffic lanes has been a constant in the field research carried out worldwide, with immediate results in the publication of numerous scientific articles [some of them being presented in the following].

Wu et al. developed a CNN-based method for traffic lane recognition from video camera images [61]. The method is built on three levels: the first level is perception, the second level is the decision-making part and the last level is developed for controlling the vehicle (Figure 15). The second layer determines the lane using CNN using the method based on the short-term memory of the network, and the determination [lane position] is used to estimate the future trajectory of the vehicle. In the last level, a steering command is generated based on the information determined by the previous levels.

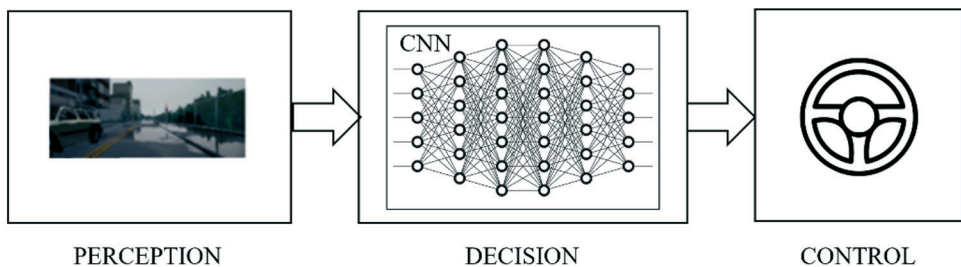


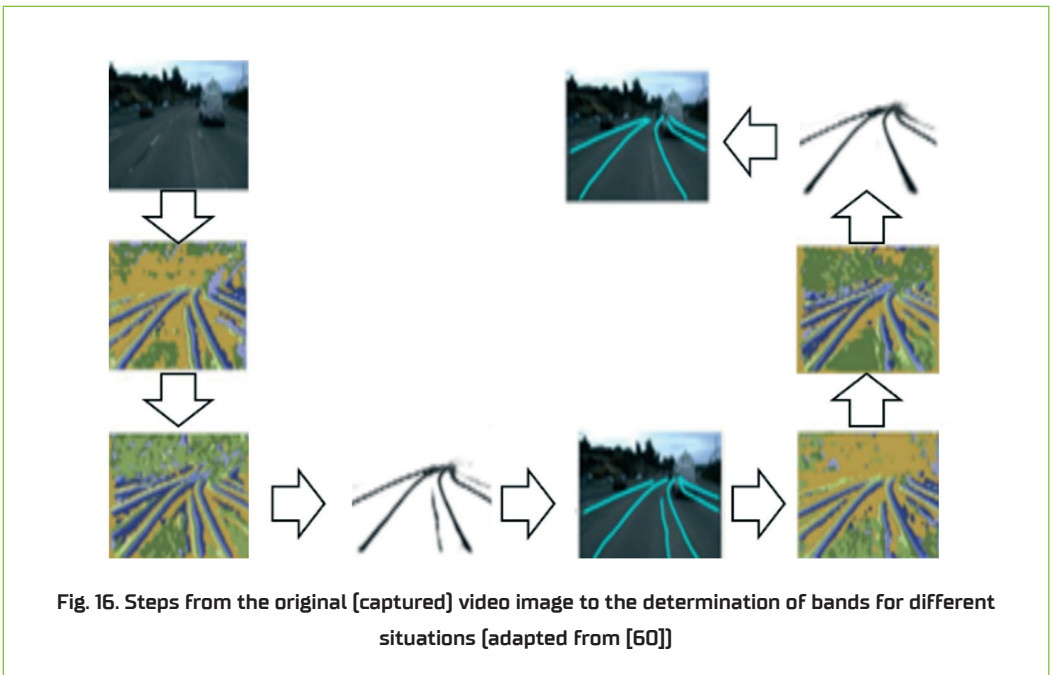
Fig. 15. Vehicle direction control method based on the use of a CNN network [adapted from [61]]

Similarly, Sun et al. [50] developed a new DL method for traffic lane detection. Using the LaneNet software architecture, the proposed system consists of an encoder and two decoders. The two decoders together interpret results received from the encoder (with the mention that the 2 decoders are similar but differ in output size). The results show that this method outperforms the LaneNet network trained on the TuSimple database image set.

In order to avoid using post-processing to identify lanes, J. Philion presents a novel lane recognition technique based on a neural network that learns to decode landmarks directly [60]. Because the technique uses a neural network to generate the identified lines on the captured images, post-processing is completed more quickly (Table 1). Two data sets (pictures from the TuSimple and CULane databases) were used to train the network, and the outcomes show that the accuracy on these data sets was 95.2% (Figure 16).

Tab. 1. The effectiveness of the approach suggested in [60] (model "Ours") in contrast to alternative approaches.

Model	Frames/seconds
Ours	90.31
H-Net	52.6
CULane	17.5
PolyLine-RNN	5.7
EL-GAN	<10



Dawam and Feng proposed a road surface marking detection system based on recorded images [62], thus creating an additional layer of data that can be used by the automatic vehicle driving system. The authors used the YOLOv3 object detection algorithm, which was trained to recognize 25 different road surface markings using over 25,000 images for training. The experiment results show that this model has an accuracy of 98.28% and a detection speed from 20 ms to 41.05 ms.

Muthalagu et al. proposed a computationally efficient way by dividing the detection process between two neural networks with a simple structure [63]. A CNN is trained to segment the lane markings, and the second network determines the coordinates of the critical points of the markings. As a final step the key points are linked to determine the solid lines and the left and right lanes of the vehicle (Figure 17).

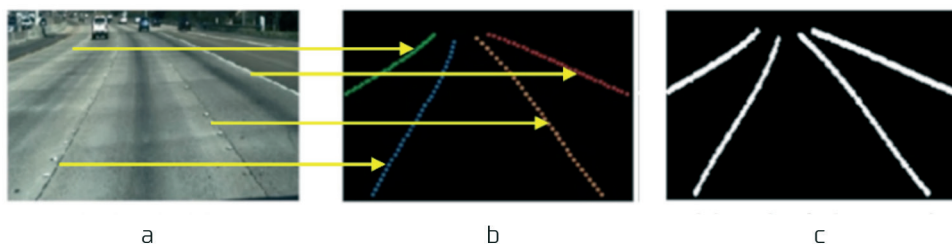


Fig. 17. The process of detecting traffic lanes by using a two neural networks [a-video image, b-setting critical points, c-traffic lines drawing] (adapted from [63])

- **Deep Learning methods combined with geometric modeling methods.**

A number of studies have combined geometric modeling techniques with the DL method to improve the effectiveness of lane marking detection on the road. Neural networks have demonstrated the ability to attain high accuracy percentages and response times that are low enough for real-time vehicle use on manually labeled data sets. The lack of labels applied to the collected data restricts the usage of the algorithms in complex traffic scenarios. To solve this problem, Yousri et al. [64] propose the combination of classical techniques based on image processing with neural networks to deal with complex traffic situations (Figure 18). To begin with, the images from the nuScenes data set are passed through various image processing methods. The first step is to remove the distortions from the captured image, after which an adaptive extraction of the region of interest takes place using the VMD (Vertical Mean Distribution) method. Strip extraction from the image is performed using the probabilistic progressive Hough transformation (PPHT), and to filter out unwanted information, the image is transformed into an aerial perspective. The Canny filter is then used to deal with arbitrary traffic lane shapes discovered in the photographs and subsequent color space conversion and morphological processes ensure accurate traffic lane segmentation.

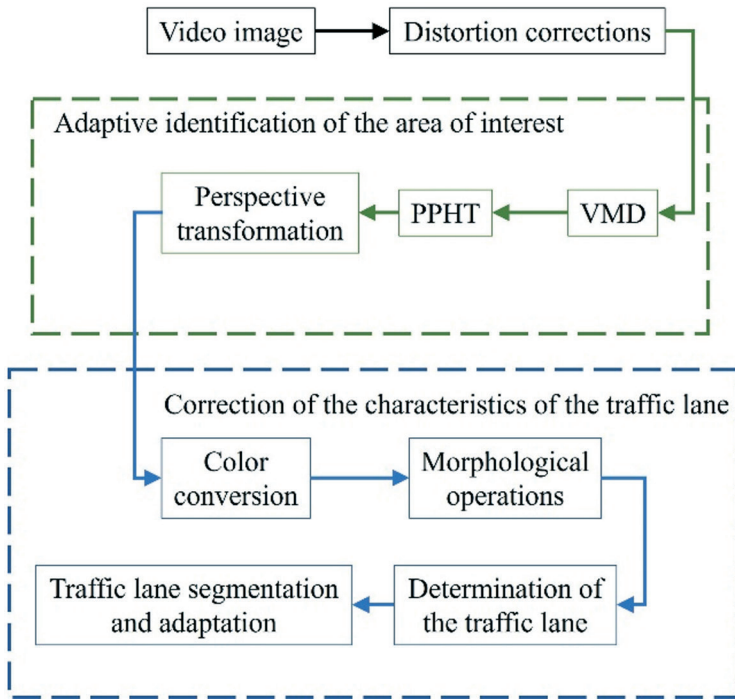


Fig. 18. Algorithm for detection of traffic lanes from images with complex traffic situations [adapted from [64]]

The brighter areas of the picture are separated from their darker surrounds using the morphological process. Subsequently, a search is employed to repeatedly iterate over various line shapes and identify lines of arbitrary shapes more quickly. Lastly, the labels are applied to the photos and the images are converted back to standard view using the inverse perspective transformation. The paper's main contributions are the introduction of robust traffic lane detection through overall image analysis and the first application of the state-of-the-art ResUNet++ architecture [based on convolutional neural networks] for traffic lane detection (it outperformed the other tested models). Techniques for identifying traffic lanes often take a long time, need more processing power, and include intricate algorithms to examine the minute details of captured photos. A CNN neural network architecture to address this problem and which avoids the complexity of existing techniques is presented in Figure 19 [65]. Consequently, CNN is thought to be a feasible approach for lane marking prediction; however, tweaking and fine-tuning network hyper-parameters is necessary for better results. This work uses S-Shaped Binary Butterfly (SBBOA), a heuristic optimization approach, to enhance and optimize CNN design. The algorithm used to define the CNN architecture reduces the occurrence errors (prevents the overfitting or underfitting of the network) of interpretation in the traffic lanes determination. Methods for determining the

hyper-parameters of the CNN network using SBBOA is shown in Figure 19. The TUSimple and CULane databases are used to evaluate the proposed SBBOA-CNN model. The experimental findings obtained demonstrate that the suggested strategy surpasses other state-of-the-art strategies in terms of classification accuracy and traffic lane determination accuracy.

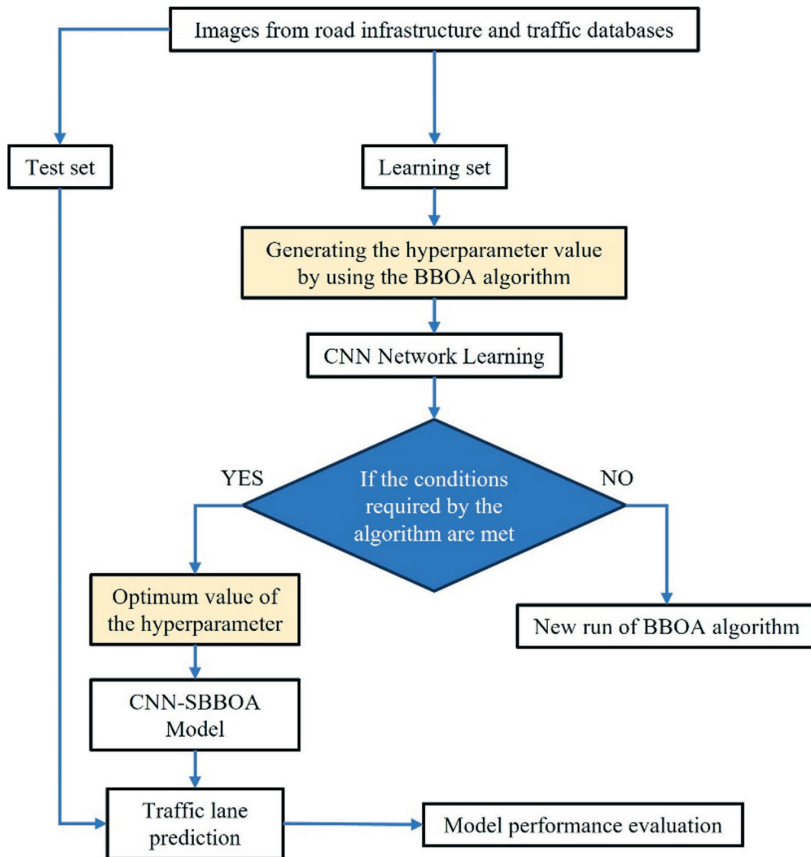


Fig. 19. Algorithm of using SBBOA-CNN method in traffic lane detection [adapted from [65]]

• Deep Learning methods combined with Machine Learning methods

Deep Learning [DL] methods used together with Machine Learning [ML] methods increase the efficiency of algorithms used in lane detection, since the efficiency and accuracy in lane detection of feature-based methods is limited due to several constraints (the number of lanes of traffic is not well determined, confusion of poles with traffic lanes, unfavorable weather or inadequate lighting) [39].

The approach of the mixed use of the two AI methods consists in the first step by mapping from the two-dimensional image recorded by the camera [2D] to the three-dimensional image [3D] taking into account also the distortion of the video camera. Thus, for all points on the recorded image, the distance can be determined. To reduce the necessary calculation, only the regions of interest were chosen for analysis (by training an SVM – Support Vector Machine model). The SVM model is trained with the data obtained from each image by extracting the gradient histograms from the area with the lane and from the area without the traffic lane, according to the process shown in Figure 20.

Detection of the traffic lane markings is performed by a two-stage CNN, where the establishment of the points associated with the traffic lanes has a greater weight for the determination of the lanes. The method was tested on a dataset taken from the TuSimple database, showing an operating accuracy of 96.97% [Figure 21]. The potential of using a high-resolution automotive radar sensor and a neural network [SegNet algorithm] to perform traffic lane segmentation was demonstrated in the study [66]. Influences of different input datasets and network layers on the segmentation performance was also analyzed, and methods and directions for improving the segmentation results were proposed (using Bayes' theorem). A prototype frequency modulated continuous wave (FMCW) radar was used which can measure: distance, relative speed, angle and reflection magnitude of objects.

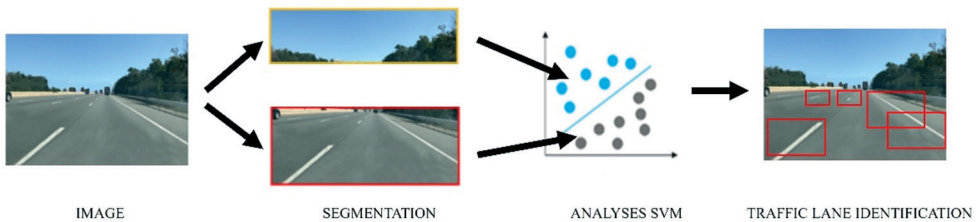


Fig. 20. Image segmentation for the area with bands and the area that does not contain relevant information [without bands] [adapted from [66]]



Fig. 21. The way to determine the lanes by establishing the points associated with the traffic lanes in different environmental situations, by the method proposed in [66]

A two-dimensional fast Fourier transformation (FFT) is applied to the signals obtained from the radar to obtain the reflection points from the base signal. A clustering algorithm is also used to group points into objects and label them. The SegNet algorithm used was connected to a CNN which consists of an encoder and a decoder. The neural network is trained with synthetic data generated by a radar simulator and the results obtained are compared with real data collected from a highway and test circuits. It was found that the proposed method can determine the driving corridor (the area between the road barriers, but attention! not the traffic lanes) and the vehicles in traffic on a highway with high accuracy (Figure 22).

Two other researchers, Pihlank and Riid, developed and applied a new method for determining traffic lanes and road edges, also based on the use of neural networks [67]. A specific combination of encoder, residual network and densely connected network architectures was proposed. The actual method consists of using three identical neural networks that process RGB images of road surfaces and produce binary masks for determining road edges and markings (traffic lanes). The method was evaluated on a dataset of orthoframe photos of Estonian highways and shows high accuracy (over 90%) for both road edges and road surface marking detection.

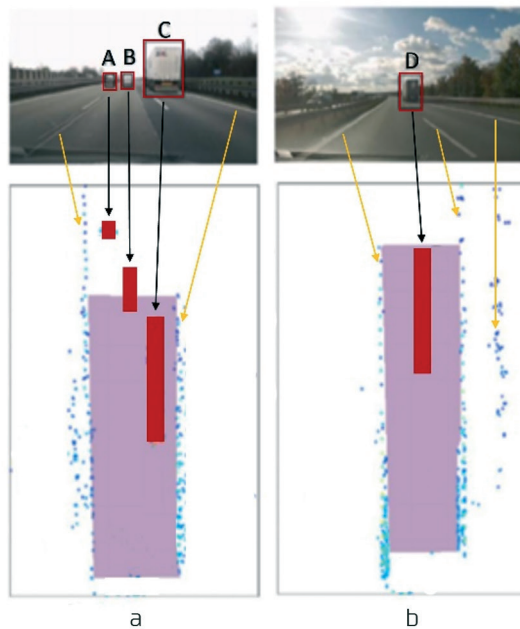


Fig. 22. Results obtained regarding the detection of the driving corridor and the vehicles on a highway according to the method proposed in [67] (a) for close-up image and congested traffic, b) for distant image)

5. Conclusions

The most important conclusion that can be drawn following the study carried out and previously presented on the methods and methodologies for detecting traffic lanes, is that based on current research in the future it is necessary to continue, develop and apply new algorithms, methods and methodologies that to improve the virtual transposition of the road and traffic conditions into mathematical models to help the vehicle control system to understand the traffic situation. The need to increase the degree of complexity of ADAS systems, in parallel with the increase in their reliability and ease of integration within the vehicle's control and command systems, leads to the increase and diversification of research on the vehicle systems to better and highly accurately understand every traffic situation. Within the traffic lane detection process, it can be observed that the research follows two specific directions: the first being related to the geometric modeling of traffic lanes and their related markings and the 2nd through the implementation of specific artificial intelligence techniques applied to images captured over from traffic. The last example has limitations related to image capture performance, image capture technologies, and the need to remove potential errors resulting from the vehicle's external environment of use (traffic volume, unique features of the road infrastructure, weather, and environmental conditions, etc.). The main issue that still needs to be resolved is striking a balance between the functionality of ADAS systems for identifying traffic lanes and the hardware required to carry out the necessary command and control functions, considering factors like costs, implementation possibilities, reaction time and decision-making speed, etc.

6. Nomenclature

AI	Artificial Intelligence	DL	Deep Learning
AP	Automated Parking	ESC	Electronic Stability Control
ABS	Anti-Lock Braking System	FAOdM	Fully Automated On-demand Mobility
ACC	Adaptive Cruise Control	FAPV	Fully Automated Personal Vehicle
AEB	Automatic Emergency Brake	FFT	Fast Fourier Transformation
ADAS	Advanced Driver Assistance Systems	FMCW	Frequency Modulated Continuous Wave
APA	Angled Parking Assist	HT	Hough Transformation
AVP	Automated Valet Parking	IMU	Inertial Measurement Unit
AHWC	Automated Highway Cruising	IPM	Image Perspective Mapping
BAS	Brake Assist System	ISA	Intelligent Speed Adaptation
BSW	Blind Spot Warning	LDW	Lane Departure Warning
CNN	Convolutional Neural Network	LEVEL I	Attention and warning
CW	Collision Warning	LEVEL II	Assistance
DAS	Driver Assistance Systems		
DM	Driver Monitoring		

LEVEL III	Partial/conditional automation	RNN	Recurrent Neural Network
LEVEL IV	Total automation/Autonomy	ROI	Region of interest
LIDAR	Laser imaging, detection, and ranging	SBBOA	Heuristic optimization algorithm
LKA	Lane Keep Assistance	TCS	Traction Control System
ML	Machine Learning	TJA	Traffic Jam Assist
NV	Night Vision	TSD	Traffic Sign Detection
PD	Pedestrian Detection	V2X	Vehicle-to-Everything
PAS	Parking Aid System	V2I	Vehicle-to-Infrastructure
PPA	Parallel Parking Assist	V2V	Vehicle-to-Vehicle
PPHT	Probabilistic Progressive Hough Transformation	VMD	Vertical Mean Distribution
RANSAC	Random sample consensus algorithm		

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