Advanced Driver-Assistance Systems: A Path Toward Autonomous Vehicles

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Advanced Driver-Assistance Systems

A path toward autonomous vehicles.

By Vipin Kumar Kukkala, Jordan Tunnell, Sudeep Pasricha, and Thomas Bradley

Advanced driver-assistance systems (ADASs) have become a salient feature for safety in modern vehicles. They are also a key underlying technology in emerging autonomous vehicles. State-of-the-art ADASs are primarily vision based, but light detection and ranging (lidar), radio detection and ranging (radar), and other advanced-sensing technologies are also becoming popular. In this article, we present a survey of different hardware and software ADAS technologies and their capabilities and limitations. We discuss approaches used for vision-based recognition and sensor fusion in ADAS solutions. We also highlight challenges for the next generation of ADASs.

OVERVIEW OF AUTOMOTIVE SYSTEM SAFETY

Safety in automotive systems has been a major concern since the early days of on-road vehicles. Several original equipment manufacturers (OEMs) have attempted to address this issue by developing various safety systems to protect occupants within a vehicle as well as prevent injuries to people outside the vehicle. These systems are mainly classified into two types: 1) passive (or reactive) and 2) active (or proactive). Passive safety systems protect vehicle occupants from injuries after a crash, e.g., seat belts, air bags, and padded dashboards. Due to a consistent consumer demand for safer vehicles, passive safety systems that have been under continuous development for many decades have been augmented by active safety systems, which seek to prevent a crash from

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happening altogether. Active systems are one of the main areas of interest and have seen major growth in today's vehicles. Examples of such systems include lane keeping, automatic braking, and adaptive cruise control. These systems are commonly known as *ADASs* and are becoming increasingly popular as a way for automotive manufacturers to differentiate their offerings while promoting consumer safety.

Recent studies from the World Health Organization indicate that 1.25 million deaths occur every year due to road traffic accidents [1]. Moreover, such accidents in recent years have an annual global cost of US$518 billion, which takes away approximately 1–2% of gross domestic product from all of the countries in the world [2]. These high fatality rates, monetary losses, and increasing customer demand for intelligent safety systems are some of the key reasons for OEMs to develop ADASs. Moreover, with the increasing number of electronic control units and integration of various types of sensors, there are now sufficient computing capabilities in vehicles to support ADAS deployments. The different types of sensors, such as cameras, lidar, radar, and ultrasonic sensors, enable a variety of different ADAS solutions. Among them, the vision-based ADAS, which primarily uses cameras as vision sensors, is popular in most modern-day vehicles. Figure 1 shows some of the state-of-the art ADAS features and the sensors used to implement them.

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Modern-day ADASs are also key technologies to realize autonomous vehicles [3]. But several challenges with the design, implementation, and operation of ADASs remain to be overcome. Some of these challenges include minimizing energy consumption, reducing response latency, adapting to changing weather conditions, and security. In this article, we provide a synopsis of the landscape of ADAS research and development to address these challenges.

ADAS TAXONOMY

We propose a taxonomy of ADASs based on the type of sensors they use (Figure 2), as discussed next.

VISION SENSORS

Cameras are the most commonly used vision sensors in vehicles. Vision-based ADAS uses one or more cameras to capture images and an embedded system to detect, analyze, and track different objects in them. In high-end ADAS, cameras are used to monitor both the inside and outside of the vehicle. Camera integration in modern vehicles is becoming more common because of its low cost and easy installation. At the 2018 Consumer Electronics Show, Mobileye stated that it is introducing smart cameras in millions of cars hitting the streets in 2018. In addition, laws such as [4] (that mandate all vehicles manufactured from 1 May 2018 onward use vision-based ADAS) will further aid in camera integration. Cameras capture information such as color, contrast, and texture, which gives them a unique advantage over other sensors. Two types of cameras are often used in vision-based ADAS: 1) monocular and 2) stereo.

MONOCULAR CAMERAS

These camera systems have only one lens. As these systems have only one image output at any point of time, they have low image-processing requirements compared to those of other camera types. These cameras can be used for multiple applications, such as the detection of obstacles, pedestrians, lanes, and traffic signs [5]. They can also be used for monitoring the driver inside a vehicle, e.g., for face- and eye-detection and head-pose analysis [23]. But monocular camera images lack depth information and are, therefore, not reliable sensors for distance estimation. Some techniques [5] allow approximating distance by identifying key features in the captured image frame and tracking their position when the camera is in motion.

STEREO CAMERAS

These systems consist of two or more lenses, each with image sensors, separated by a certain distance (known as *stereo base*). Stereo cameras are useful in extracting three-dimensional

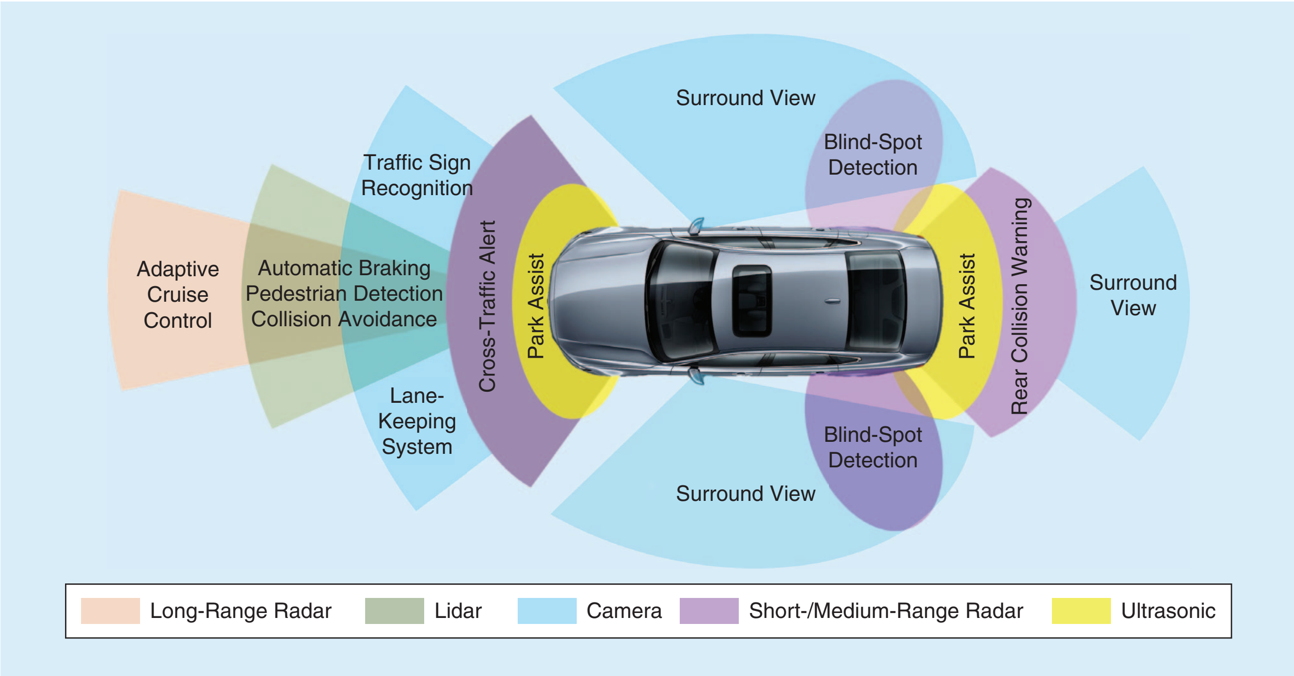

FIGURE 1. The state-of-the-art ADAS sensors used.

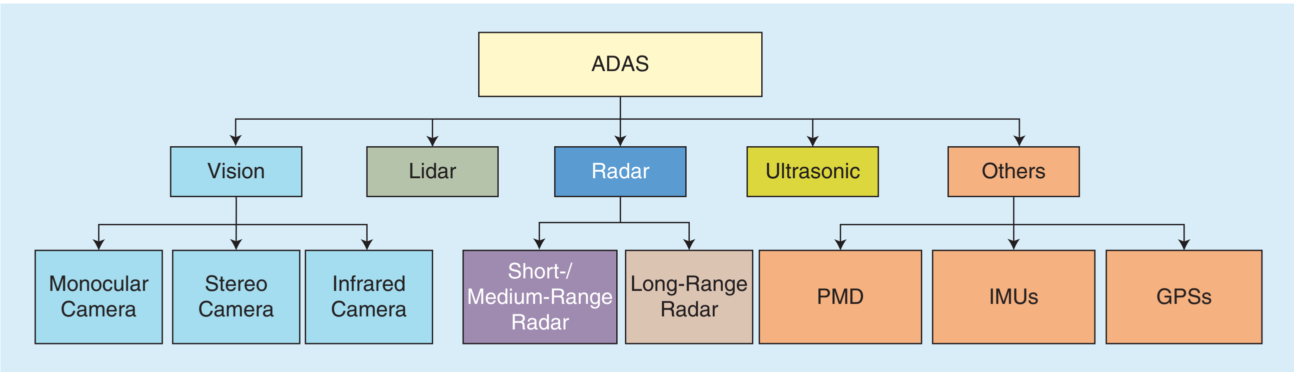

FIGURE 2. The taxonomy of an ADAS. PMD: photonic mixer device; IMUs: inertial measurement units; GPSs: global positioning systems.

(3-D) information from two or more two-dimensional images by matching stereo pairs (images from left and right sensors) and using a disparity map to estimate the relative depth of a scene. These cameras can be used for a variety of applications, such as traffic sign recognition, lane, pedestrian, and obstacle detection as well as distance estimation, with much greater accuracy compared to monocular cameras.

Stereo systems can be relied upon for accurate distance (depth) estimation over short distances, up to 30 m. In most production vehicles with stereo cameras, the cameras are located inside the vehicle, behind the rear-view mirror, angled slightly downward, and facing the road.

IR CAMERAS

There are two main types of IR cameras. Active IR cameras use a near-IR light source (with wavelengths from 750 to 1,400 nm) built in the vehicle to illuminate the scene (which cannot be seen by the human eye) and a standard digital camera sensor to capture the reflected light. Passive IR cameras use an IR sensor, where every pixel on the IR sensor can be considered as a temperature sensor that can capture the thermal radiation emitted by any material. Unlike active IR cameras, passive IR cameras do not require any special illumination of the scene. Still, popular night-vision solutions mainly use active IR cameras to assist the driver by displaying video data on a screen during low light conditions.

LIDAR

Lidar works by firing a laser beam at an object and then measuring the time taken for the light to bounce back to the sensor, to calculate the distance of an object. These systems can achieve high-resolution 3-D images and operate at longer ranges than camera systems. Some of the lidar scanners support surround-view sensors (that fire laser beams continuously in all directions), which can generate a 360° 3-D image of the surroundings with extremely accurate depth information (as shown in Figure 3). Lidar is becoming very popular in autonomous vehicles. Several prototype vehicles [8], [9] have demonstrated the advantages of using lidar in autonomous driving. Lidar is useful for systems implementing automatic braking, object detection, collision avoidance, and more. Depending on the type of sensor, lidars for cars can have a range of up to 60 m. Despite the aforementioned advantages, lidars are heavy, bulky in size, and expensive. Moreover, atmospheric conditions such as rain or fog can impact the coverage and accuracy of these systems. Emerging solid-state lidars [10] have opened the possibility of powerful lidars that are significantly smaller and relatively inexpensive.

RADAR

Radar systems emit microwaves and estimate the speed and distance of an object by measuring the change in the frequency of the reflected wave as per the Doppler effect. Due to the longer wavelength of microwaves, they can travel much farther than optical light (e.g., with lidar) and can detect objects at a longer distance. Unlike lidar, radar is not affected by foggy or rainy weather conditions and is relatively inexpensive. Depending on their operating distance range, radar systems can be classified as short range (0.2–30 m), medium range (30–80 m), or long range (80–200 m) [11]. Cross-traffic alerts and blind-spot detection are some of the applications of short-/medium-range radars. These systems are often located at the corners of a vehicle. Adaptive cruise control is a long-range radar application, with the system located behind the front grill or under the bumper. Researchers have been developing algorithms to improve the performance of radar and reliability all while attempting to reduce the cost and power of the system [6].

ULTRASONIC SENSORS

Ultrasonic sensors use sound waves to measure the distance to an object. These sensors are mainly used for detecting objects very close to the vehicle. Some example applications include automatic parking and parallel parking assist. These sensors are mainly located under the front and rear bumper of the vehicle.

OTHERS

A few other sensors are used to complement and improve the functionalities of those discussed earlier. For instance, photonic mixer device (PMD) cameras consist of an array of smart sensors that enable fast optical sensing and demodulation of incoherent light signals simultaneously [12]. PMDs can support parallel target pixel-wise distance measurement without scanning, thus resulting in faster imaging, high lateral resolution, and depth information. IMUs and GPSs are examples of systems that help improve the distance measurements with lidar and radar.

VISION-BASED ADASs

Vision-based ADASs rely on images from cameras and use computer vision principles to extract useful information.

COMPUTER VISION DATA FLOW FOR ADASs

Figure 4 shows the steps involved in a vision-based system, each of which is discussed.

IMAGE ACQUISITION

This refers to the process of capturing a frame from a video. The frame is often represented as a matrix of pixel data where each frame contains three channels of information, e.g., red, green, and blue (RGB) sets of pixels. Typical frame rates in ADASs range from five frames per second (fps) to 60 fps depending on the application. Applications that involve detection of vehicle proximity need a higher frame rate due to the rapid change in distance for cars on the road. In contrast, traffic sign detection does not demand a higher frame rate because only one frame of the sign needs to be captured for the sign to be detected.

PREPROCESSING

There are several common preprocessing steps needed to prepare an image for various computer vision algorithms, e.g., denoising, color enhancement, color space conversion, and image stabilization. A typical example of color space conversion is to convert the RGB color space to hue, saturation, and value to separate color from the intensity. Moreover, the hue channel is often used to separate out adverse effects (e.g., shadows, uneven lighting, and over- and underexposure) in the image to make tracking and detection easier.

SEGMENTATION

This is the process of separating features from a frame. In analyzing an image, it is helpful to partition it into recognizable objects, e.g., identifying the road and sky in a frame as

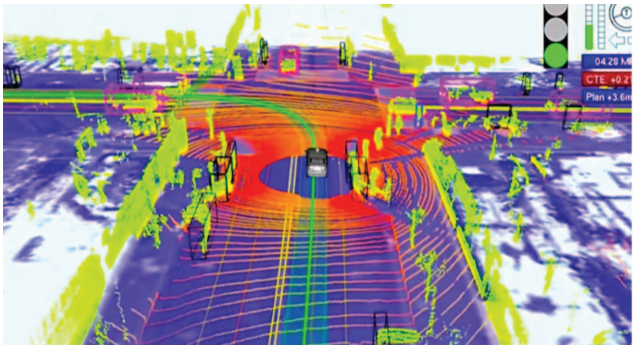

FIGURE 3. The Google self-driving-car-generated 3-D image of its surroundings using lidar [9].

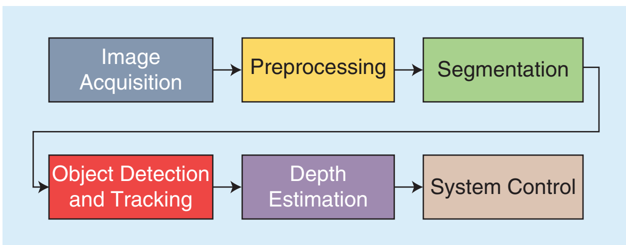

FIGURE 4. The vision data flow for the ADAS used.

IMUs and GPSs are examples of systems that help improve the distance measurements with lidar and radar.

two different features. Various thresholding techniques are used to filter one class of pixels (e.g., the road) from another (e.g., the sky). One of the methods, e.g., exploits color information to detect a stop sign, where an algorithm may look for red in the image (typical for stop signs in the United States). Any pixels in that red range will be turned white, and anything that is not will be turned black, as shown in Figure 5(a). This results in a binary image that is often used as a mask for finding the area of interest on the original image.

OBJECT DETECTION AND TRACKING

This is the process of classifying an object in an image (e.g., determining if an object ahead is a vehicle, sign, or pedestrian) and predicting its movement. It is often accomplished with various machine-learning (ML) algorithms. ML algorithms are provided large training data sets (thousands of images) to learn and differentiate between vehicles and common objects found around them. An example of an object detection method is called the *cascade classifier*, which was first presented in [13] for face detection, on low-performance hardware systems.

Another common technique to train and classify images is using a convolutional neural network (CNN), which typically consists of an input layer, multiple hidden layers, and an output layer. The hidden layers consist of convolution and pooling layers that are used for feature extraction and a fully connected layer for classification. Examples of CNN frameworks used for vision applications include Caffe, Darknet, and MATLAB. An application of a CNN for object tracking is discussed in [14]. Kalman-filter-based object tracking is proposed in [15], where the filter tracks the object's velocity.

DEPTH ESTIMATION

This step involves estimating the distance of an object in the image frame relative to the camera. There are two common methods for depth estimation: 1) the use of a stereo camera to create a stereo pair and develop them to make a depth map and 3-D point cloud that allow a real-world reconstruction of the scene [16]; and 2) the use of a monocular camera and several state-of-the art techniques that use a subset of optical flow, calibration, and least squares techniques [17].

SYSTEM CONTROL

This is the last step in the vision data flow, which involves interpretation of the outputs from previous layers, as shown in the vision data flow diagram in Figure 4. This step requires a weighing of each layer in the vision pipeline to come up with a confidence value that can be used to make decisions. A major challenge at this step is a false detection with high confidence that would take priority over other information obtained from the previous layers. Thus, training with data that is correct and contains many orientations of the object to be classified is crucial to achieve high accuracy.

OUTDOOR MONITORING

In this section, we will discuss the classification of objects that are outside a vehicle, e.g., pedestrians, vehicles, and roads.

PEDESTRIAN DETECTION

Detecting pedestrians is done using various classifiers, e.g., [18]. Often more than one classifier is used for detecting people because of the varying orientation and configuration in which pedestrians may appear. Deep-learning networks such as CNNs have been helpful to not only identify pedestrians but also classify their actions.

VEHICLE DETECTION

Vehicle detection is a major focus of object detection in ADASs. The fact that many vehicles share common features, such as having tires, brake lights, and license plates, allows the detection of these objects to indicate the presence of a car. These features are all used to distinguish the vehicle from other objects, such as signs, roads, and other miscellaneous objects. In Figure 6, an example of vehicle detection is shown, using a CNN framework (Darknet) and a real-time detection system, You Only Look Once [19]. The orientation

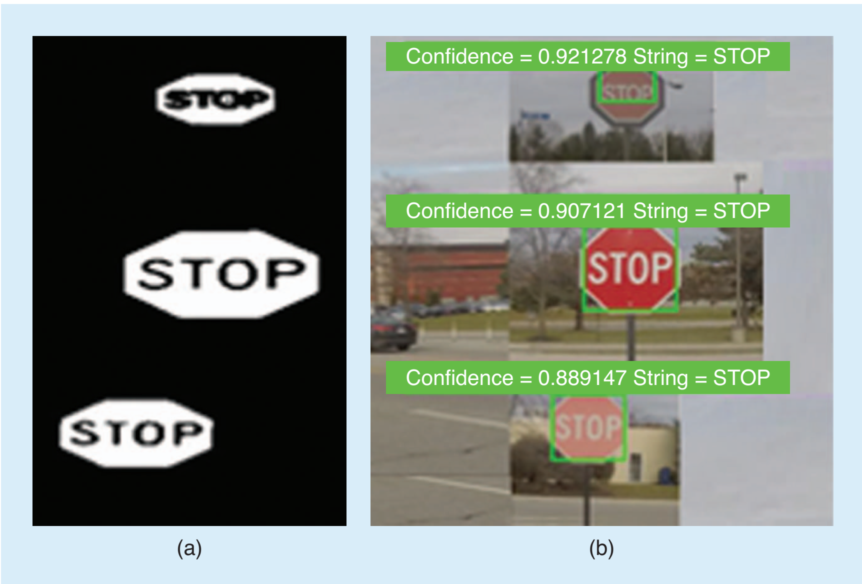

FIGURE 5. The stop sign detection: (a) a binary stop sign and (b) stop sign classification using optical character recognition.

of vehicles can cause some issues with their identification. A vehicle being viewed from the front contains a different set of features than a vehicle from the side or back. Often vehicle classifiers consider various classes of vehicles, such as cars, trucks, and semis that are trained with many orientations.

SIGN DETECTION

Many ADASs are beginning to support traffic sign detection. The most common use case is determining the speed limit on the road by reading a speed sign (an ADAS would alert the driver if the vehicle speed is over the limit). For instance, color thresholds can be used to find the location of a sign and optical character recognition to determine what that sign displays [as shown in Figure 5(b)]. Other methods include using CNNs and hybrid techniques, such as [20].

LANE DETECTION

Another ADAS feature used in a few production vehicles is the ability to keep the vehicle within the lane lines on the road (illustrated in Figure 6). However, lane lines are one of the hardest road features to detect because of their inconsistencies, such as being different colors, faded, and sometimes not even present. Current methods to detect lane lines often use a Canny transform to find the edges in the image. Once the edges are found, a Hough transform is used to compare the lines to a single slope to determine if they are indeed lane lines [21]. The use of CNNs is also becoming popular for lane line detection.

COLLISION AVOIDANCE

ADASs are beginning to incorporate automatic braking and collision avoidance. This is done by combining many features discussed earlier, such as object tracking, vehicle detection, and distance estimation [14]. With this combination of data, a vehicle can predict a collision and stop it from happening by braking or even steering out of the way.

INDOOR MONITORING

In a study conducted by the National Highway Traffic Security Administration [22], it was observed that driver fatigue, drowsiness, or distraction are the causes of 80% of vehicle accidents. As ADAS becomes prevalent in production vehicles, there has been an increase in focus on monitoring the driver using a camera pointed at him or her. If the driver accesses a phone or does not look at the road for a specific time duration, an alert or attempt to get off the road will be made [23]. Drowsiness-fatigue-detection systems have also included the ability to detect if the driver has fallen asleep and can attempt to alert the driver though a sequence of seatbelt vibrations and speaker alerts [24].

NEXT-GENERATION ADASs

Next-generation ADAS solutions are beginning to use sensor fusion and other advanced communication systems, such as vehicle-to-everything (V2X).

> One of the major problems with today's ADASs is that the performance of the system is significantly impacted by changing environmental and weather conditions.

SENSOR FUSION

Sensor fusion refers to combining information from multiple homogenous or heterogeneous sensors to find a single best estimation of the state of the environment. Fusion helps sensors complement each other's limitations and offers greater leverage to the system compared to a system with individual sensors. Sensor fusion offers high precision, reliability, robustness to uncertainty, extended spatial and temporal coverage, and improved resolution, which are crucial in safety-critical systems, such as vehicles. Although this comes at a higher computation cost, the computation power available in modern-day cars and the reducing cost of the sensors are facilitating the widespread integration of these systems.

The classification of different levels of sensor fusion along with the most commonly used techniques for fusing data are discussed in [25]. The growing interest in deep learning and other ML methods in recent years has driven researchers toward exploring more efficient and intelligent techniques that enhance ADASs with sensor fusion capabilities.

V2X COMMUNICATION

V2X communication represents a class of communication systems that provides the vehicle with an ability to exchange information with other systems in the environment. Examples include vehicle-to-vehicle (V2V) for collision avoidance, vehicle-to-infrastructure (V2I) for traffic signal timing, vehicle-to-network for real-time traffic updates, and vehicle-to-pedestrian for pedestrian signaling. State-of-the-art V2X communication is based on either dedicated short-range communications (DSRC) or cellular networks [26]. The IEEE 1609 family of standards for Wireless Access in Vehicular Environment (WAVE), which is developed based on the IEEE 802.11p standard, defines an architecture and a set of services and interfaces to enable DSRC-based secure V2V and V2I communication [27].

FIGURE 6. The object (lane, vehicle, and sign) detection.

> Modern vehicles are becoming increasingly connected with a lot of different systems, such as Wi-Fi, near-field communication, and V2X.

AUTONOMOUS VEHICLES

Next-generation ADASs using sensor fusion and V2X communication are paving the way for autonomous driving. The Society of Automotive Engineers (SAE) J3016 standard [28] defines six different levels of driving automation for on-road vehicles (see Table 1). A vehicle is categorized as level zero if there are no ADASs assisting the driver in handling steering and acceleration/deceleration and everything is handled manually by the driver. Level one vehicles consist of ADASs assisting the driver in handling either steering or acceleration/deceleration under certain cases with human driver input. ADASs in level two vehicles handle both steering and acceleration/deceleration under certain environments with human driver input. In general, in lower-level vehicles (levels zero to two), the driver monitors the driving environment. In contrast, ADAS monitors the driving environment in higher-level (levels three to five) vehicles. Modern vehicles with the top-of-the-line ADASs, such as the 2016 Tesla model S, are level three, where multiple safety systems are handled by the system, but the driver intervenes when needed. Level four vehicles handle multiple safety systems and operate in a wider range of environments. Level five automation is the end goal of autonomous driving, where all of the systems in the car are operated by the ADAS, under all driving conditions (such as snow-covered roads and unmarked dirt roads) and would not require any human intervention. This, however, still requires significant advances in multiple areas, such as sensor technology, computing systems, and automotive networks.

CHALLENGES WITH ADASs

Despite significant advances in the field of ADASs, several important challenges remain to be overcome.

Table 1. SAE J3016 levels of driving automation [28].

SAE Level	Definition	Monitoring of Driving Environment
Zero	No automation	Human driver
One	Driver assistance	
Two	Partial automation	
Three	Conditional automation	System
Four	High automation	
Five	Full automation	

CHANGING ENVIRONMENTAL CONDITIONS

One of the major problems with today's ADASs is that the performance of the system is significantly impacted by changing environmental and weather conditions. For example, vision-based ADASs have issues with sensing during rainy and extreme lighting conditions (too dark and/or too bright) [30]. One of the possible solutions to this problem includes sensor fusion, by relying on other sensor data depending on the weather conditions, e.g., relying on the camera and radar during low light conditions while using the camera and lidar during other times for accurate distance estimation. The inclusion of V2I and developing cost-effective smart roads could help mitigate this issue.

RESOURCE-CONSTRAINED SYSTEM

Embedded systems used in ADASs have a requirement for low power consumption. This is because ADASs involve running several complex algorithms that result in high power consumption and thermal dissipation. Due to the limited availability of energy in vehicles, it is essential to minimize the power consumption of the embedded system used in ADASs. Using more energy-efficient hardware than conventional general-purpose central processing units is important, which is why emerging ADAS hardware must rely on graphics processing units, digital signal processors, image signal processors, etc., that are customized to reduce power consumption for ADAS applications. Moreover, as the embedded systems for ADAS operate in real time, they have strict timing constraints, which establishes a latency minimization requirement. Hence, optimized hardware and software that results in minimal power consumption and greater performance (lower latency) predictability are highly desired in an ADAS.

SECURITY

Modern vehicles are becoming increasingly connected with a lot of different systems, such as Wi-Fi, near-field communication, and V2X. This enables the vehicle to sense and receive a variety of information but also makes it more vulnerable to attacks. Many vehicle hacks have been demonstrated, e.g., researchers in [7] used onboard diagnostics (OBD-II) to hack a GM vehicle. In [29], the telematics system in a Jeep Cherokee was hacked to accelerate, brake, and kill the engine. This problem is aggravated in ADASs and autonomous driving. Preventing hackers from gaining access to connected vehicles is becoming increasingly important. This involves securing both in-vehicle networks and external communication.

GEOSPATIAL CONSTRAINTS

Many of the modern ADAS solutions being developed are tested within a geographic location or a group of locations where they are sold. This limits the ADAS to one or a certain group of geographical locations. This is because not all countries (or some states in a country) adhere to the same sign and road conventions uniformly, which makes ADAS algorithms that are often trained under one location hard to work efficiently in other locations. There is a need to improve algorithms, e.g., by exploiting V2X technology deployments to overcome variations in road sign conventions.

CONCLUSION

In this article, we presented a detailed survey of different types of ADAS variants and an overview of the sensors used in these variants. We described a classification of ADASs based on the different types of sensors used and discussed outdoor and indoor monitoring with vision-based ADASs. The importance of sensor fusion techniques and advanced communication systems, such as V2X, and their importance for emerging autonomous vehicles was also discussed. Finally, we presented some important unresolved challenges with ADASs that must be addressed going forward.

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