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Camera systems – key technology for ADAS in autonomous vehicles

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Advanced Driver Assistance Systems (ADAS) have become an integral part of modern vehicles, with the potential to significantly enhance safety on the road. ADAS technology involves the use of sensors, algorithms, and software to assist drivers and provide them with real-time information about their surroundings, traffic conditions, and potential hazards. Sensors utilized for object tracking and environmental detection, particularly those based on laser, radar, and camera technologies, are fundamental to the functional performance of ADAS. Within automotive applications, the majority of camera systems are equipped with wide-angle or fish-eye lenses, both of which are known to introduce substantial optical distortion. To ensure accurate environmental perception, particularly in the context of geometric feature recognition and distance estimation, such cameras require meticulous calibration. Therefore, this paper describes a case study concerning cameras used in vision-based ADAS, as well as the most frequently used calibrating techniques. It describes the fundamentals of camera calibration and implementation, with results given for different lenses and distortion models. By engaging with this article, readers will gain a comprehensive understanding of the technological foundations, functional principles, and practical challenges associated with camera-based ADAS that need to be addressed to ensure its safe and effective operation on the road. The article serves as a technical reference that not only enhances the reader's theoretical knowledge but also informs practical decision-making in the development of safe and effective driver assistance systems.

Key words: *automotive camera, ADAS, advanced driver assistance systems, autonomous vehicles, camera systems*

1. Introduction

In the context of the development of autonomous driving, an automated and connected vehicle is nowadays taken as the basis. With the advancement of the Internet and wireless communication connections, the possibilities for networking vehicles are also increasing. The range of infotainment systems is growing through the use of Bluetooth connections, navigation systems receive immediate traffic jam and closure information, and smartphone apps can be operated directly via the multifunction display. In the near future, mobile online services are to be expanded so that the customer can purchase additional functions and assistance systems similar to an app store after buying the vehicle [6].

The first assistance systems in vehicles were introduced to increase the stability of the vehicle: an electronic stability program (ESP) and an anti-lock braking system (ABS). To date, a large number of informative, supportive, and warning systems have been added. The primary goal is to make traffic safer and to avoid accidents or reduce the severity of accidents through the widespread installation of ADAS.

The five levels of driving automation serve as a basic classification of ADAS. The differentiation is made by evaluating the shares that the driver and the system take on the driving task [22].

The driving task is divided according to the three-level hierarchy of Edmund Donges into navigation, lane guidance, and stabilization. The navigation task includes choosing a suitable route with an estimate of the required time, while the driver draws conclusions from the upcoming traffic situation for adjusting, for example, the target lane and target speed during lane guidance. In the context of the stabilization level, the driver performs corrective interventions so that the control deviation is stabilized and reduced to an acceptable level [8].

Level 0, Driver only, is understood as driving without assistance systems. This means that the driver takes on the entire driving task themselves. They perform longitudinal and lateral control continuously. The lowest degree of automation is level one. Within limits, it is possible for the system to take over either longitudinal or lateral control, while the driver performs the other task. The second level, also called partial automation, includes systems that can take over both lateral and longitudinal guidance. The driver must monitor the traffic and their vehicle at all times to take over vehicle control in case of danger. This also includes a system failure. The current state of technology can largely be classified into these two categories. In the case of the third level, the driver no longer has to monitor the traffic and their vehicle continuously, but must be able to follow a takeover request. This is because the system recognizes its limits but is not able to return to a risk-minimal state in every situation. The driver can also decide to take over control again at any time. Systems of the fourth and fifth level, fully autonomous, should be able to return to a risk-minimal state without any driver intervention. Problems for implementation arise not only from immature technology but also from the driver's behavioural obligations, which they must fulfil when driving [10].

As perception and vision is key for ADAS operation to be successful, this work covers details on specific applications of camera-based driver assistance systems and the resulting technical needs for the camera system. Use cases covering the outside of the vehicle are shown. The basis of every camera system is the camera module with its main parts – the lens system and the image sensor. The underlying technology is described, and the formation of the camera image is discussed. Moving to the system level,

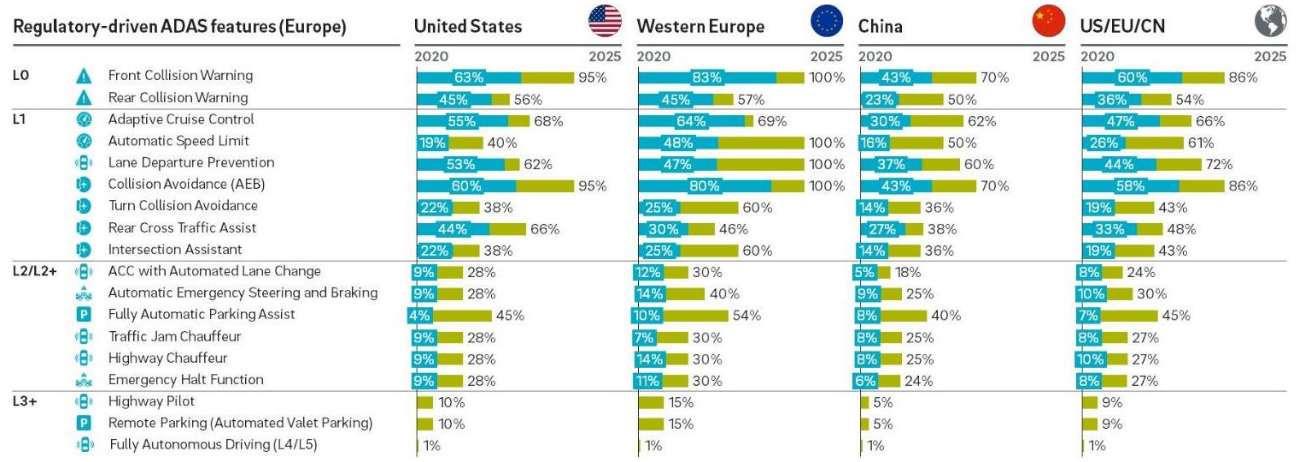

Fig. 1. Percentage of features installed on vehicles by region [17]

basic camera architectures, including mono and stereo systems, are analysed.

ADAS capabilities are classified according to six distinct feature levels, ranging from Level 0 to Level 5:

Level 0: Basic level encompasses fundamental warning systems, including front and rear collision alerts, blind spot detection, and lane departure warnings. These features are increasingly incorporated into modern vehicles either as standard equipment or available as optional add-ons.

Level 1: Driver assistance level offers support functionalities such as automatic emergency braking, adaptive cruise control, lane-keeping assistance, distance control, automated speed regulation, driver interaction aids, and collision avoidance technologies.

Level 2: Partial automation involves the concurrent deployment of adaptive cruise control and lane-keeping capabilities. It also includes advanced cruise features, automated emergency steering and braking, as well as fully autonomous parking functionalities.

Level 3: Conditional automation enables vehicles to manage highway driving autonomously, including executing automatic lane changes and remote parking manoeuvres. These systems offer comprehensive environmental sensing and do not require driver input during specified operational scenarios, such as travel from the highway entrance to the exit.

Level 4: A High automation level represents highly autonomous driving capabilities, enabling vehicles to operate without human oversight in certain defined scenarios. Currently, no production vehicles offer Level 4 automation, nor have any such systems been officially announced for commercial release.

Level 5: Full automation enables vehicles to operate entirely autonomously under all conditions, eliminating the need for any human driver intervention. As of now, no Level 5 systems are commercially available, and their market readiness is not anticipated before 2030 or 2035 at the earliest [22].

Due to regulatory requirements, Europe grows and leads overall ADAS features. Notably, European Union legislation has stipulated that as of 2024, all newly manufactured vehicles must be equipped with both front-facing cameras and radar sensors as standard components. For instance, the integration rate of collision warning systems increased from 83% in 2020 to a projected 100% by 2025. Similarly, the adoption of automated speed limiters rose from 48% to complete implementation over the same period. Lane departure prevention systems also saw significant growth, with usage doubling to 100% by 2025.

On a global scale, forecasts for 2025 indicate that 14% of the world's vehicles will lack any ADAS features, while 40% are expected to support Level 1 functions, 36% will incorporate Level 2 capabilities, and approximately 10% will be outfitted with Level 3 or more advanced systems. Overall, these figures represent a substantial increase in ADAS deployment compared to current levels, as illustrated in Fig. 1.

The objective of this article is to provide a structured review of automotive camera systems as a fundamental technology in ADAS, with a focus on their architecture, calibration techniques, and sensor performance. Emphasis is placed on both monocular and stereo camera configurations, as well as static, dynamic, and learning-based calibration methods essential for accurate perception.

The significance of this work lies in its relevance to current challenges in ADAS development, where precise sensor operation and reliable environmental interpretation are critical for vehicle safety. By synthesizing technical knowledge and recent advancements, the article offers valuable insights for researchers and engineers working on vision-based autonomous systems.

2. Advanced driver assistance systems in vehicles

2.1 Methodology

The study is based on a qualitative engineering analysis of camera systems used in ADAS. The authors conducted a comprehensive literature review using various databases. Based on the gathered data, the authors analysed the technological components of mono and stereo camera systems, focusing on architecture, image quality factors (resolution, colour, dynamic range), and calibration needs. The paper presents a synthesis of calibration models with a practical emphasis on their applicability in ADAS platforms. Furthermore, the authors discuss emerging trends in real-time and deep learning-based calibration, highlighting their significance for future development.

2.2. Overview and function

Advanced Driver Assistance Systems technology is designed to assist drivers and enhance safety on the road. It does this by using sensors, algorithms, and software to collect data about the vehicle's surroundings and provide real-time information to the driver.

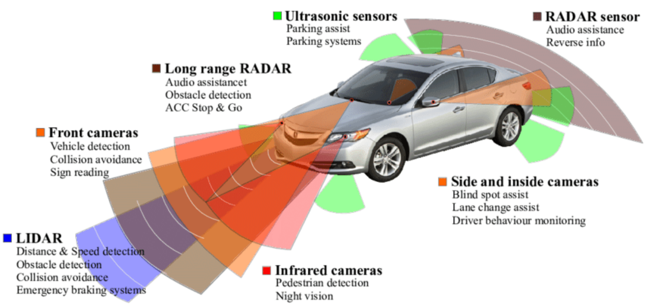

Fig. 2. Sensors used in ADAS – including camera, radar, LiDAR, and ultrasonic components [16]

ADAS technology relies on various sensors (Fig. 2) to collect data about the vehicle's environment. These sensors include cameras, radar, LiDAR, and ultrasonic sensors. Cameras are used to capture visual data, such as lane markings, traffic signs, and other vehicles. Radar sensors use radio waves to detect the position and speed of objects in the vehicle's path, while LiDAR sensors use laser beams to create a detailed 3D map of the surroundings. Ultrasonic sensors use sound waves to detect the distance between the vehicle and nearby objects.

The data collected by the sensors is used and analysed by algorithms of ADAS to make real-time decisions. These algorithms can detect potential hazards, such as a vehicle in the driver's blind spot, and alert the driver with visual or auditory cues [9].

ADAS technology relies heavily on software to control the various components of the vehicle. This software is responsible for processing the data collected by the sensors and executing the algorithms that control the brakes, steering, and other systems. The software must be designed to be reliable, secure, and easy to update as new features are added or improved [10].

2.3. Calibration of ADAS

ADAS calibration and recalibration is the precise physical alignment, testing, and electronic aiming of sensors. In newly manufactured vehicles, ADAS sensors are accurately installed and configured according to predefined factory specifications, ensuring that each sensor is precisely oriented as intended. However, over the operational lifespan of a vehicle, various incidents such as collisions, minor accidents, or repairs involving adjacent components, can result in the misalignment of these sensors. When such misalignments occur, it becomes essential to recalibrate the affected systems to restore them to their original, pre-incident condition, thereby ensuring that the sensors continue to perform in accordance with their intended design specifications. Depending on the configuration of the vehicle's ADAS platform and the guidelines established by the original equipment manufacturer (OEM), calibration may involve static procedures, dynamic procedures, or a combination of both [12].

The calibration of ADAS components, particularly camera systems, is a critical process that directly affects the accuracy and reliability of environmental perception. Calibration refers to the precise determination and adjustment of sensor parameters to ensure correct spatial interpretation of the environment and accurate data fusion in multi-sensor systems. In the context of camera-based ADAS, two primary categories of calibration are typically distinguished: intrinsic and extrinsic.

Intrinsic calibration involves the estimation of internal camera parameters, such as focal length, principal point, skew coefficient, and lens distortion coefficients. These parameters describe how the camera projects three-dimensional world points onto the two-dimensional image plane. Since most automotive camera systems employ wide-angle or fisheye lenses to maximize field of view, they are subject to substantial optical distortions. Therefore, the accurate modeling and correction of radial and tangential distortions is essential to enable reliable image interpretation and subsequent object detection and tracking [7].

Extrinsic calibration, on the other hand, refers to determining the position and orientation of the camera with respect to a known reference frame, typically the vehicle coordinate system or another sensor in a multi-modal configuration (e.g. radar, LiDAR). This step is fundamental for accurate sensor fusion, allowing the combination of data streams from different modalities into a coherent representation of the environment. Errors in extrinsic calibration can result in significant misalignment of perceived objects and deterioration of system performance.

Depending on the ADAS platform and the manufacturer's specifications, calibration procedures are generally divided into static and dynamic approaches, each with distinct methodologies, requirements, and operational contexts [22].

Static calibration is performed in a controlled environment, typically within a workshop or service center, and involves the use of predefined reference targets and precise positioning of the vehicle. This method relies on physical calibration patterns, such as checkerboards, dot matrices, or specific 2D/3D markers, which are placed at exact distances and orientations relative to the vehicle. The calibration system then captures images of these patterns using the onboard camera sensors and computes the intrinsic and extrinsic parameters through mathematical optimization techniques, such as Zhang's method [24] or bundle adjustment algorithms. Static calibration provides high repeatability and accuracy, making it the preferred choice during manufacturing, sensor replacement, or major maintenance procedures. However, it requires dedicated equipment, ample workspace, and trained personnel, which may limit its applicability in field conditions.

Dynamic calibration, in contrast, is performed during actual vehicle operation and does not depend on dedicated calibration targets. Instead, it uses environmental features such as lane markings, traffic signs, curbs, or roadside infrastructure, which are detected and analyzed by the vehicle's sensors in real time. Advanced computer vision and machine learning algorithms are employed to identify these features and estimate sensor parameters by observing their geometric consistency over time and motion. Dynamic calibration is particularly advantageous in post-service scenarios or when minor sensor misalignments occur during regular use, as it eliminates the need for workshop visits and minimizes vehicle downtime. However, it may be influenced by variable lighting conditions, road quality, or temporary occlusions.

3. Cameras for ADAS

3.1. Mono camera architecture

Cameras represent the most widely utilized type of vision sensor in automotive applications. In vision-based ADAS, one or more cameras are employed to capture visual data, which is subsequently processed by an embedded computing system to identify, analyse, and track various objects within the scene. Cameras provide critical information, including colour, contrast, and texture, granting them a distinct advantage over alternative sensor technologies. They are capable of delivering high-resolution outputs across spectral, spatial, and temporal dimensions, thereby enabling comprehensive environmental perception. Moreover, certain specialized systems offer extended functionalities, such as night vision capabilities or distance estimation. The following sections present a systematic overview of automotive camera systems, including their underlying technology and structural configurations.

In vision-based ADAS, two principal types of cameras are commonly employed: monocular and stereo systems. An illustrative example of a standard monocular camera architecture for a front-facing application is provided in Fig. 3. In this configuration, the camera module is interfaced through a communication bus, and the image data is transmitted via a parallel connection to a dedicated image processing unit. In the described setup, a digital signal processor (DSP) is implemented to perform real-time video processing. Alternatively, some systems may incorporate field-programmable gate arrays (FPGA) or application-specific integrated circuits (ASIC) to fulfil similar processing requirements [24]. The image processing unit is supported by high-speed memory modules, which serve not only to temporarily store processed image data but also to retain multiple image frames – particularly useful for implementing object tracking algorithms. A microcontroller oversees various support functions, including exposure regulation, control of the windshield heating element, communication via the in-vehicle bus system, and additional system monitoring and management tasks. Interaction between the microcontroller and the digital signal processor is facilitated through an interprocess communication (IPC) interface.

Monocular cameras are characterized by the presence of a single optical lens. Due to the production of only one image stream at any given time, these systems demand relatively modest computational resources for image processing when compared to other, more complex camera configurations. Such cameras are versatile and can be employed in a range of applications, including the detection of obstacles, lane markings, and traffic signs [4]. In addition to external monitoring, monocular cameras can also be used within the vehicle cabin for driver observation tasks, such as facial recognition, eye tracking, and head pose estimation [14]. However, a notable limitation of monocular imaging systems is their inability to capture depth information directly, rendering them less suitable for tasks that require precise distance measurement. Nevertheless, certain algorithmic approaches [4] have been developed to approximate depth by identifying key features in the captured image and tracking their position, particularly when the camera is in motion.

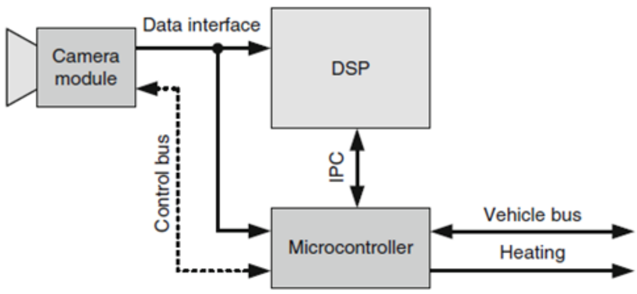

Fig. 3. Architecture of a mono camera system [23]

3.2. Stereo camera

3.2.1. Stereo camera architecture

The basic structure of a stereo camera system is illustrated in Fig. 4. In this architecture, both image sensors are governed by a single microcontroller, which manages the acquisition and coordination of visual data. The captured image signals are subsequently transmitted to the DSP and a FPGA for preliminary processing.

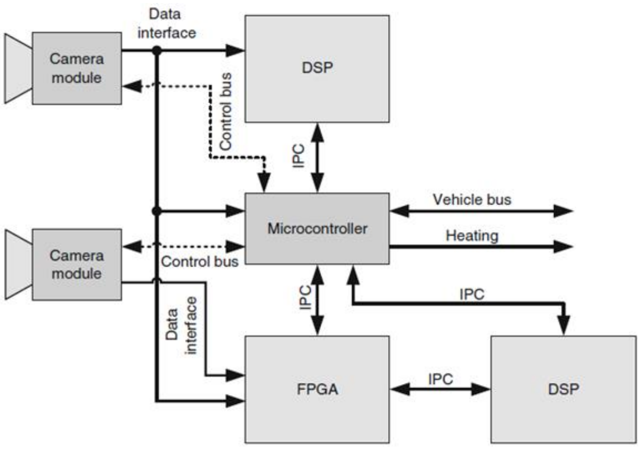

Fig. 4. Architecture of a stereo camera system [23]

The FPGA is responsible for executing critical preprocessing tasks, including image rectification, the generation of disparity maps, and the calculation of optical flow. The DSP then performs object recognition functions, such as identifying pedestrians, vehicles, and other relevant features within the visual scene. A second DSP is often dedicated to performing specific ADAS functionalities, such as lane departure warning and traffic sign recognition. Communication between the stereo vision system and the vehicle's internal network is facilitated by a microcontroller interface. Each of the image processing units is linked to high-speed memory modules, which are used to support rapid data access and temporary storage during computation [19].

Stereo camera systems are composed of two or more camera modules, each containing its own image sensor, and positioned at a fixed distance from one another – a parameter referred to as the stereo base.

These systems are particularly effective in generating three-dimensional (3D) spatial information by comparing pairs of two-dimensional images acquired from the left and right sensors and constructing a disparity map to calculate relative depth within the scene. Stereo vision systems can be applied across a wide range of use cases, including the detection of traffic signs, lane boundaries, pedestrians, and obstacles, as well as accurate estimation of object distances, achieving significantly higher precision than monocular camera systems [23]. To ensure accurate 3D perception, the alignment of the two camera modules must be precisely calibrated across all spatial axes, including pitch, yaw, and roll, prior to their integration into the housing. Even minor deviations in the alignment of the optical axes can lead to miscalibration, ultimately impairing the functionality of the entire stereo vision system.

Image-based techniques provide a rapid and cost-effective approach for acquiring high-quality 3D representations, especially when compared to more expensive alternatives such as radar and LiDAR systems. Continual advancements in image resolution and sensor quality have transformed digital cameras into affordable, highly reliable tools capable of generating detailed 3D data. As a result, stereo cameras have become indispensable components in autonomous vehicle systems, offering a practical solution for real-time depth estimation, as illustrated in Fig. 5. The accurate reconstruction of dense depth maps is a fundamental requirement for numerous ADAS tasks, including obstacle detection, free-space identification, vehicle localization, environmental mapping, path planning, and lane boundary recognition [11].

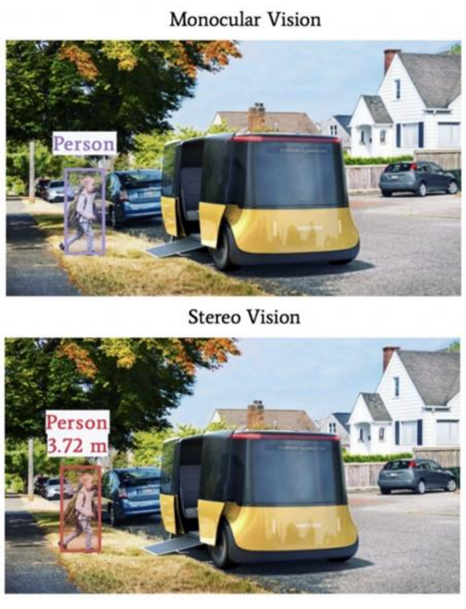

Fig. 5. Comparison between monocular and stereo vision systems for depth estimation [18]

3.2.2. Structure of a camera system

A basic camera architecture is shown in Fig. 6. In this arrangement, an object or scene is projected through an imaging lens, which focuses the optical information onto an image sensor. The sensor is composed of an array of pixels, each of which converts incident photons into electrical signals, which are then transmitted to a processing unit for analysis. If the processed output is intended for immediate user interpretation, it is subsequently rendered on a display screen.

In the development of a camera system, it is essential to conduct a thorough evaluation of both its individual components and the integrated system as a whole. The optical lens is a critical element that significantly influences the overall performance of the camera. It directly impacts a range of imaging parameters, including achievable resolution, the extent of the field of view, depth of field, colour fidelity, and the system's light sensitivity. Given that optical assemblies inherently introduce imperfections, such as image distortion, appropriate correction mechanisms must be applied to ensure accurate image reproduction. The optical image captured by the lens is subsequently converted into digital signals by the image sensor. Consequently, careful coordination and design optimization between the optical system and the image sensor are vital to achieving high image quality. The sensor itself plays a central role in defining several critical attributes of the final image, including resolution (determined by pixel count), field of view (influenced by pixel count and arrangement), dynamic range, colour accuracy, and, most notably, the sensitivity to light [15].

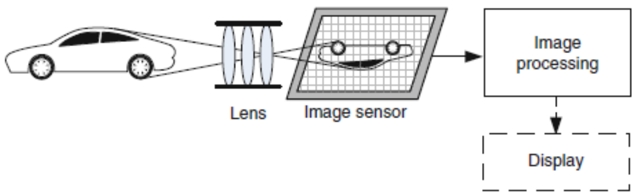

Fig. 6. Basic camera architecture [23]

Field of view

The field of view (FOV) of a camera plays an important role in the application and is essentially defined by the lens and the image sensor (Fig. 7). One distinguishes the field of view in horizontal and vertical direction (HFOV, VFOV).

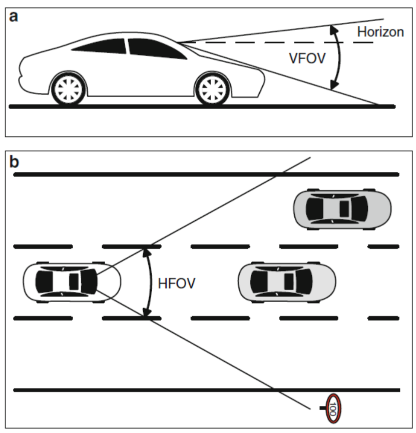

Fig. 7. Vertical (a) and horizontal (b) field of view of a front view camera [23]

Depending on the requirements of the camera, the maximum field of view that the system can monitor is important [6]. A distinction is made here between horizontal and vertical fields of vision. Front view camera systems, such as the multifunctional camera considered in this work, require relatively large HFOV values in case of lane detection (in tight curve scenarios) and object detection. The vertical field of view is determined primarily by the mounting height and the minimum detection distance at close range [7].

Resolution

Optimal image resolution results from the coordinated interaction between the optical system, the image sensor, and the image processing unit. The resolution capacity of the sensor is primarily determined by both the physical size and the total number of pixels it contains. Under low-light conditions, sensors with smaller pixel dimensions tend to produce images with increased noise levels when compared to those with larger pixels, thereby diminishing the system's dynamic response capability. To effectively utilize small pixel architectures, high-precision optical components, specifically lenses with high resolving power, are required to maintain image sharpness. Without such high-quality optics, the system may produce images with a high pixel count but lacking in meaningful structural detail due to blurring. Additionally, the use of small pixel sensors necessitates extremely accurate mechanical alignment of the sensor within the optical path, as such configurations inherently exhibit a significantly reduced depth of field.

On the other hand, as the light-sensitive surface area of an image sensor increases, the system's ability to distinguish finer image details also improves. However, increasing the sensor size also leads to higher production costs and greater physical dimensions, both of which pose limitations in the context of ADAS applications where compactness and cost-efficiency are critical considerations [23].

For driver assistance systems involved in environmental perception, a typical specification entails a resolution greater than 15 pixels per degree of field of view. Among these applications, traffic sign recognition imposes particularly stringent requirements on image resolution, especially when the accurate interpretation of additional characters or symbols is necessary. This concept is illustrated in Fig. 8, which demonstrates how varying resolution levels affect the legibility of traffic signs. While the general shape and warning symbols remain discernible at lower resolutions, the identification of supplementary pictograms or textual information becomes increasingly difficult or impossible. In the context of driver monitoring applications, even higher image resolutions may be required, particularly for functions such as eye tracking that rely on the precise detection of subtle facial features [13].

Fig. 8. Effect of decreasing resolution using the example of a traffic sign (480 × 650/72 × 96/36 × 48/24 × 32/18 × 24/12 × 16) [23]

Colour

In the area of advanced driver assistance systems, complementary metal-oxide-semiconductor (CMOS) image sensors, commonly employed in automotive imaging, are primarily responsive to the visible (VIS) and near infrared (NIR) regions of the electromagnetic spectrum. To enable differentiation across colour channels, these sensors incorporate colour filters that segment incoming light into its constituent spectral components.

Colour fidelity offers substantial advantages in both front-view and surround-view camera applications. In surround-view systems, a lifelike visual representation on the driver's display is essential for intuitive scene interpretation.

Conversely, in front-view systems, the capacity to accurately distinguish between discrete colour channels plays a critical role, particularly in the detection of features such as lane markings, as illustrated in Fig. 9.

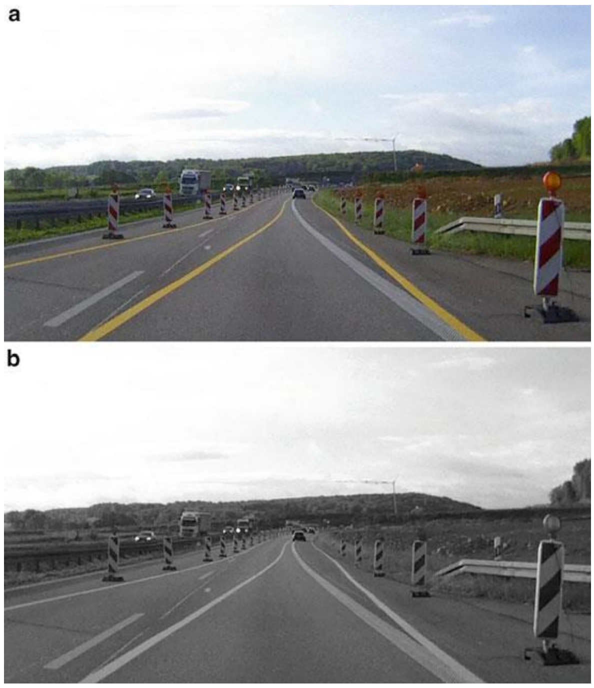

Fig. 9. Importance of colour separation for the detection of lane markers without filtering (a) and with filtering (b) [23]

Dynamic range

The dynamic range (DR) of a camera system defines its ability to simultaneously capture details in both low-light and high-intensity regions within the same image frame. More specifically, it is quantified as the ratio between the luminance of the darkest and the brightest pixels that the sensor can accurately record.

In dark areas, the dynamic range is limited by the noise limit of the image sensor, and in bright areas by the saturation limit of the image sensor. In addition to the image sensor, the dynamic range of the camera lens and the optical path define the overall system dynamic range [1].

The dynamic range of the lens is adversely affected by stray light. In addition, effects such as ghosting and flare can occur, which reduce the image quality, especially in strong front light situations. For stationary objects, the dynamic range can be increased using a so-called high dynamic range (HDR) function (Fig. 10). To do this, several images of the object with different exposures are taken and put together in a very short time. Since the series of images is taken at a different time, this function is not appropriate for moving objects. The same applies to images taken while a vehicle is moving [3].

Fig. 10. Illustration of a traffic scene with a high dynamic range [23]

Noise

A camera's dynamic range and sensitivity are affected by the "noise" of the sensor. The most common cause of the noise is the so-called dark current. In this case, electrons are triggered and read out incorrectly, for example, due to thermal processes in the pixel. The magnitude of this current increases with temperature and exposure time. For this reason, it is often necessary to cool camera systems or provide sufficient ventilation. Another source of noise is the readout noise, which occurs when electrons are converted into voltage [21].

3.2.3. Image sensor technology

There are two fundamental architectures of digital image sensors for image processing: charge-coupled device (CCD) and complementary metal oxide semiconductor (CMOS). Image sensors are able to convert incident photons into electrical charges. The technology is based on the photoelectric effect, which generally refers to the release of electrons from metallic surfaces through the incidence of light. A distinction is made here between the interior and the exterior photo effect.

The external photo effect describes the phenomenon where electrons are released from a metal when photons hit it. The frequency of the electromagnetic radiation must exceed the characteristic limit frequency of each metal. Above this frequency, electron emission occurs even at very low light intensity [20].

In the case of the internal photo effect, the electrons only detach from their molecular structure, but not from the material. If the energy of the photons is greater than the energy difference between the valence and conduction bands of the photodiode material, the electrons are raised into the conduction band. Free electrons and positively charged holes are created. The change in electrical conductivity can be recorded [2].

A CCD sensor consists of a large number of light-sensitive semiconductor elements arranged over a surface. These semiconductor elements are pixels, individual photodetectors that capture the incident photons of light and convert them into an electrical signal. During the exposure time, the released electrons are collected in a potential well. The accumulated amount of charge is proportional to the intensity of the incident light and the exposure time [21]. To do this, the released charges must be transported to an A/D converter through many small steps, vertical and horizontal shift registers.

Charge-coupled device (CCD) sensors are available in several distinct architectural configurations, including interline transfer CCDs, full-frame CCDs, and frame transfer CCDs. Among these, the interline transfer CCD offers a notable advantage through its use of an "electronic shutter" mechanism, which enables the rapid acquisition of multiple images per second as well as extremely short exposure times. To facilitate this function, each light-sensitive pixel is paired with an adjacent non-photosensitive unit, which serves as a temporary memory cell. This memory cell is equipped with a cover and a light-blocking shield to prevent any additional light exposure, thereby preserving the integrity of the stored charge. Once the exposure phase concludes, the accumulated charges are swiftly transferred from the active pixels into the shielded memory cells. Subsequently, these charges are sequentially read out through vertical and then horizontal shift registers. At the end of this readout chain, the signal is amplified and converted into a voltage for further image processing purposes [21].

Similar to charge-coupled device (CCD) sensors, complementary metal-oxide-semiconductor (CMOS) sensors operate on the principle of the photoelectric effect, whereby incident photons are converted into electrical charges. The primary distinction between CMOS and CCD technologies lies in the method by which the captured electrical signals are transmitted and processed. In CMOS architecture, each photodiode is paired with a parallel capacitor that accumulates charge generated by the incoming photocurrent. The resulting voltage across this capacitor is directly proportional to the intensity of the incident light and the duration of exposure. Unlike CCD sensors, where collected charges are sequentially transferred to a centralized readout amplifier, CMOS sensors assign an individual amplifier to each pixel. which directly provides the analogue signal processor with this capacitor voltage. In the case of CMOS sensors, several transistors are associated with the light-sensitive diodes, which convert the accumulated charges into measurable voltages. As a result, pixels can be read independently without the need for serial charge transfer, as is required in CCD-based systems. The advantage of this architecture is a reduction in blooming effects, which can occur under conditions of overexposure. However, a notable drawback is that the inclusion of additional transistors within each pixel reduces the effective light-sensitive area, thereby diminishing the sensor’s overall light collection efficiency. Consequently, CMOS sensors may exhibit inferior performance in low-light environments, as less image information is captured [5]. Nonetheless, like their CCD counterparts, advanced CMOS sensors are capable of discharging all pixels simultaneously, capturing an image, and proceeding with synchronous readout. To implement global shutter functionality, additional transistors must be integrated into each pixel, which further reduces the available photosensitive surface area and may negatively impact image quality.

A CMOS sensor, like many others, can only distinguish between black and white. To enable colour recognition, colour filters are needed that divide the light into the primary colours red, green and blue. Ultimately, only one of the colours is supplied to each pixel.

4. Future directions

Since camera sensors have their advantages and shortcomings, the integration of multiple heterogeneous sensors has emerged as a fundamental strategy for achieving robust and precise environmental perception and spatial localization. However, because these sensors are not inherently co-located within a common spatial framework, accurate calibration is required to establish their relative coordinate relationships and to effectively combine their sensing capabilities.

With the rapid advancements in deep learning technologies, online camera calibration has become increasingly feasible and operationally efficient. This calibration approach entails dynamically updating sensor parameters during operation, thereby allowing the system to adapt to changes in the camera's position or the surrounding environment. Such adaptability can be realized through the application of deep learning algorithms, which are capable of modeling the complex, nonlinear relationships between intrinsic and extrinsic camera parameters and the corresponding image data. Learning-based calibration frameworks hold significant promise for transforming practices within the automotive sector. By enhancing the precision of camera-based vision, online calibration plays a crucial role in improving the reliability of tasks such as object detection [13].

The integration of deep learning-based calibration techniques within multi-sensor platforms may substantially improve the effectiveness of sensor fusion by aligning and harmonizing data from different sources. This enhancement is particularly advantageous in complex operating conditions, including low-light environments, visual occlusions, and adverse weather scenarios. Moreover, leveraging deep learning for the calibration of multiple sensors is likely to yield more stable and accurate outcomes than those typically achieved with conventional calibration methods. These developments outline several promising directions for future research in the domain of deep learning-based camera calibration.

As this field continues to evolve, it is anticipated that numerous additional opportunities for advancement and innovation will emerge. Furthermore, the broader application of these technologies is expected to exert a transformative influence across various sectors in the years to come.

5. Conclusions

Camera systems constitute a foundational element in the architecture of ADAS and are instrumental in enabling the gradual transition toward higher levels of vehicle autonomy. Owing to their capacity to acquire high-resolution visual data, automotive cameras are employed extensively for a wide range of perception tasks, including lane detection, traffic sign recognition, object classification, and distance estimation.

This study has presented a comprehensive overview of the technical configurations and operating principles of monocular and stereo camera systems within ADAS platforms. Particular attention has been devoted to the requirements for camera calibration, which plays a pivotal role in ensuring the geometric and functional accuracy of vision-based systems. Both intrinsic and extrinsic calibration procedures are necessary to mitigate distortions and to maintain reliable environmental perception under real-world operating conditions.

The integration of camera systems into multi-sensor platforms, while offering enhanced perception capabilities, introduces additional challenges related to sensor alignment and data fusion. In this context, recent advances in deep learning have facilitated the development of online calibration methods capable of dynamically adjusting sensor parameters in response to operational or environmental variations. These approaches show considerable potential in improving the robustness and precision of vision-based ADAS functions, particularly in adverse scenarios such as low-visibility or rapidly changing lighting conditions.

Given the increasing regulatory emphasis on safety and the anticipated proliferation of ADAS features in the global vehicle fleet, further research into calibration methodologies, image processing algorithms, and sensor integration strategies is essential. Continued progress in these domains will be critical to support the deployment of reliable, scalable, and cost-effective autonomous driving technologies in the near future.

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Nomenclature

ABS	anti-lock braking system
ADAS	advanced driver assistance system
ASIC	application-specific-integrated circuits
CCD	charge-couple device
CMOS	complementary metal oxide semiconductor
DR	dynamic range
DSP	digital signal processor
ESP	electronic stability program
FOV	field of view
FPGA	field programmable gate arrays
HDR	high dynamic range
HFOV	horizontal field of view
IPC	interprocess communication
LiDAR	light detection and ranging
NIR	near-infrared
OEM	original equipment manufacturers
VFOV	vertical field of view
VIS	visible

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