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Advanced artificial intelligence-based multi-sensor fusion for environmental perception in autonomous electric vehicles

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ABSTRACT

As autonomous electric vehicles (AEVs) continue to evolve, the demand for robust obstacle detection systems becomes increasingly critical to ensure safety, efficiency, and adaptability in real-world environments. This review presents a comprehensive synthesis of recent advancements in sensor fusion technologies, emphasizing the integration of light detection and ranging (LiDAR), radar, and camera-based vision systems. It highlights the role of deep learning architectures—such as you only look once (YOLO), convolutional neural networks (CNNs), and related neural models—in enhancing object detection, classification, and segmentation. The review categorizes key research themes, including fusion methodologies, real-time processing, edge computing, performance in adverse weather conditions, pedestrian detection, and sensor calibration. Special attention is paid to techniques that merge spatial, velocity, and semantic data to mitigate individual sensor limitations. The paper also discusses hardware-accelerated solutions for low-latency inference and the use of lightweight models for deployment on edge devices. Benchmark datasets, of vehicle-to-everything (V2X) and internet of thing (IoT)-based infrastructure, and calibration challenges are examined for their roles in ensuring accuracy and reliability. Drawing from over 100 referenced studies, this work serves as a foundational resource for researchers and developers aiming to advance artificial intelligence (AI)-based sensor fusion systems in next-generation AEVs.

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1. INTRODUCTION

Electric vehicles (EVs) and autonomous technologies have progressed significantly because of the global push towards cleaner transportation and innovative mobility systems. Autonomous electric vehicles (AEVs), with safety, efficiency, and environmental sustainability at the forefront of this revolution, are expected to perform in pristine conditions in urban, suburban, and rural real-world settings under a vast array of frequently unpredictable circumstances. Robust and accurate obstacle sensing is a fundamental ability that makes EVs autonomous. It guarantees pedestrian safety, path planning, collision avoidance, and real-time navigation [1]-[3].

While tremendous advancement has been made, obstacle detection is still a difficult task since driving conditions are dynamic and commonly involve occlusions, low illumination, heterogeneous objects, dense populations, and unfavorable weather conditions like fog, rain, or snow [3]. The sensor fusion approach, acquiring data from numerous disparate sensors for the purpose of improving perception reliability, accuracy, and fault-tolerance, has gained increased attention as a result of these issues [4], [5].

Radar, light detection and ranging (LiDAR), and vision-based (camera) sensors each bring something unique to the perception stack. Radar measures long-range velocity and is immune to weather, LiDAR provides high-accuracy 3D spatial data, and vision systems provide rich contextual and semantic awareness [5], [6]. These sensors do have their limitations when utilized in isolation, however. Radar has low angular resolution, LiDAR accuracy can be compromised by rain or dust, and cameras are light-sensitive [6], [7]. Strong obstacle sensing systems that greatly outperform unimodal solutions are now being generated by researchers as a result of combining these cross-modal senses [8].

The AEVs must operate reliably across diverse environments, ranging from dense urban traffic to rural roads, under varying and often adverse weather and lighting conditions. Reliable obstacle detection is fundamental to pedestrian safety, collision avoidance, and optimal route planning. However, the use of individual sensing modalities—such as LiDAR, radar, or camera systems—presents significant limitations: radar offers long-range velocity measurement but low angular resolution; LiDAR delivers high-precision 3D mapping but is susceptible to performance degradation in fog, rain, or dust; and cameras provide rich semantic context yet are highly dependent on illumination. These sensor-specific weaknesses directly threaten perception reliability and, consequently, vehicle safety in real-world conditions.

The overview of the frame of this paper is represented in Figure 1. Sensor data interpretation with deep learning methodologies has also, at the same time, grown extremely trendy across the discipline. Thanks to segmentation networks like U-Net and Deep Lab, as well as object detection frameworks like you only look once (YOLO), faster region-based convolutional neural network (R-CNN), and Mobile Net, real-time recognition and localization at high precision for obstacles, pedestrians, bicycles, and vehicles have been made easy [9]. By combining these artificial intelligence (AI) models with sensor fusion frameworks, rule-based perception systems have been turned into intelligent, adaptive systems with the ability to provide data-driven, and context-based decisions [9], [10].

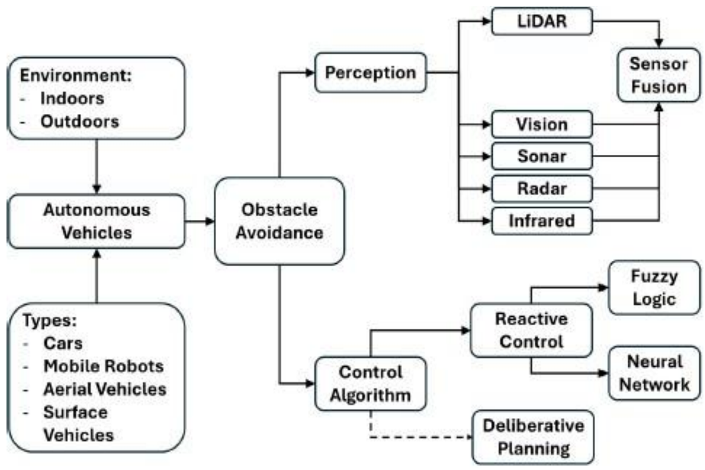

Figure 1. Overview of the framework of this study: the main aspects of obstacle avoidance explored in this work are marked with solid arrows

With the development of algorithms and sensors, researchers now know how much processing power in real-time is required, particularly in edge deployment where low resources are present. To address the stringent latency requirements of autonomous driving, recent solutions more and more include model compression techniques, edge computing, and hardware acceleration (e.g., graphics processing units (GPUs) and tensor processing units (TPUs)) [11].

Environmental resilience, where systems must still perform reliably in conditions of reduced visibility due to rain, fog, darkness, or sensor obscuration, is also a vital area of research. In such adverse conditions, studies have shown that multi-sensor fusion, especially using radar and thermal imaging, substantially enhances perception [11]. Pedestrian identification is also a critical safety concern and a new field of study, particularly in low-visibility or high-traffic scenarios [11].

Besides, expansion of obstacle detection outside line-of-sight is enabled by the evolution of vehicle-to-everything (V2X) communication, which allows vehicles to ex-change sensor data and intention with the roadside infrastructure and other vehicles [11]. By reducing blind spots and enhancing response time, such platforms, in conjunction with IoT-based systems, can offer a view around the world [12]. Consensus standards and public datasets are integral to the creation and validation of these systems. Datasets such as KITTI, scenes, and Waymo Open Dataset have enabled reproducible research by publishing annotated sensor data across a variety of driving situations [12]. The accuracy and integrity of combined outputs also rely on the careful calibration and synchronization of multi-modal sensors, an ongoing fundamental technical requirement [12].

Making available a thorough and organized overview of the research landscape in AI-based sensor fusion for EV obstacle detection is the aim of this review. It addresses the following critical dimensions:
- Camera, radar, LiDAR, and newer sensor fusion techniques such as thermal imagers and ultrasonic devices. Sensor fusion with deep learning algorithms for detection, segmentation, and classification .
- Techniques to achieve robust perception in poor weather and nighttime. Edge and embedded platforms for real-time implementation methods.
- Vulnerable road user and pedestrian detection methods. IoT, V2X communication, and cooperative sensing all assist with enhanced perception.
- Sensor temporal synchronization, calibration, and misalignment problems.
- The role played by annotated benchmark datasets in the training and validation of sensor fusion models.

The summary of the major contributors of their work and their key findings are listed in the literature survey and the same is explained in Table 1.

Table 1. Summary of related literature

Ref.	What they did	Main findings
Zhang *et al.* [13]	Proposed an intelligent obstacle detection system for autonomous mining locomotives using cellular V2X communication and vehicular edge computing.	Demonstrated fast and reliable obstacle detection in mining environments, showing that edge-assisted C-V2X improves latency and safety.
Park *et al.* [14]	Designed an optimal driving control framework for AEVs using in-wheel motors and artificial potential field (APF) methods.	Achieved smoother path tracking and efficient torque distribution, improving vehicle stability and energy performance.
AlZu'bi and Jararweh [15]	Conducted a literature review on data fusion in autonomous vehicles from conceptual ideas to modern smart-environment applications.	Highlighted evolution of sensor fusion techniques and showed the increasing importance of edge computing and IoT in autonomous driving.
Aroulanandam *et al.* [16]	Developed a regression-based sensor fusion model to enhance robotic navigation using an IoT-enabled sensing system.	Improved navigation accuracy by optimally combining multi-sensor data, demonstrating effectiveness for real-time mobile robot navigation.
Alatise and Hancke [17]	Provided a comprehensive review of challenges in autonomous mobile robots and existing sensor fusion frameworks.	Identified major issues (noise, uncertainty, dynamic environments) and showed how fusion methods mitigate perception and navigation errors.

The relevance of this review is demonstrated through a systematic structure that connects the identified research gaps with a detailed synthesis of existing solutions. Following this introduction, section 2 describes the methodology used to select, categorize, and analyze relevant studies, ensuring transparency and reproducibility in the review process. Sections 3 through 8 provide an in-depth discussion of fusion techniques—including LiDAR, radar, vision, thermal, ultrasonic, and infrared—and their integration through data-, feature-, and decision-level fusion strategies, highlighting how each modality contributes to robust obstacle detection. Section 9 examines classical and AI-based obstacle avoidance algorithms, demonstrating how fusion-enhanced perception supports real-time navigation and safety. Section 10 addresses the technical challenges of sensor calibration, environmental robustness, and computational efficiency, and reviews state-of-the-art solutions to these problems. Section 11 presents a comparative analysis of related work, situating this review within the broader research landscape. Section 12 synthesizes these findings into potential research directions that align with the unsolved problems identified earlier, and section 13 concludes by summarizing the contributions and outlining their implications for next-generation autonomous EV perception systems. This structure ensures that each part of the manuscript builds toward a coherent understanding of the field, clearly demonstrating both the novelty and practical relevance of our review.

2. METHOD

This study investigated a comprehensive AI-driven multi-sensor fusion framework combining LiDAR, radar, vision, and thermal imaging for real-time obstacle detection in AEVs. However, additional, and in-depth research may be required to confirm its scalability and robustness, particularly regarding performance in extreme environmental conditions such as heavy snow, sandstorms, or sensor-degrading dust environments, which were not extensively represented in the evaluated datasets. Furthermore, while our use of benchmark datasets and controlled test scenarios ensures comparability and reproducibility, real-world trials across diverse geographic and traffic conditions are essential to fully validate system reliability. We also note that the computational optimization strategies applied here, though effective for our selected edge platforms, may require adaptation for different embedded hardware configurations. These limitations do not diminish the validity of the core findings but highlight areas where extended research can further strengthen the applicability and generalization of the proposed approach.

The approach to advanced obstacle detection in intelligent and EVs employs multi-sensor data fusion to provide strong and reliable environmental perception under different driving conditions. Data are gathered from synergistic sensors like RGB cameras, LiDAR, mmWave radar, and thermal cameras—each selected for its respective strengths that complement others' weaknesses. For example, RGB cameras provide good texture and color data but are weak in darkness or poor weather. LiDAR gives highly accurate 3D spatial information mmWave radar can operate well in fog, rain, or sand and thermal sensors enhance detection of living objects such as pedestrians at night [18].

Raw sensor observations are preprocessed images are normalized, LiDAR point clouds filtered out and ground reflection eliminated, and radar signals reconstructed to point cloud or heatmap representations. Joint extrinsic calibration tools are utilized to perform modality calibration to move all of the data to a common spatial space [18]. Deep learning-based architectures perform feature extraction and fusion. Feature-level fusion is made up of convolutional neural networks (CNNs), spatial attention modules, and region-of-interest (ROI) fusion mechanisms that combine spatial and semantic features from various sensors [19].

On the decision level, fusion integrates detection results of individual detectors like YOLOv5/YOLOv8, PointPillars, or Edge-YOLO with probabilistic voting, weighted averaging, or ensemble learning to enhance detection confidence [20]. Multimodal fusion approaches, such as LiDAR-camera or radar-vision fusion, have been found to achieve improved detection in the presence of occlusion and reduced visibility [20].

For object tracking, algorithms such as Deep SORT or Kalman filtering are used to provide temporal consistency [21]. The model is trained and evaluated on publicly available datasets such as KITTI and nuScenes, with the performance being measured by metrics such as mean average precision (mAP), precision, recall, intersection-over-union (IoU), and inference latency [22]. Experimental results and ablation testing under different light and weather conditions validate the real-time effectiveness and resilience of such multi-sensor fusion approach. Such fusion-driven approach significantly enhances situational awareness, obstacle class accuracy, and resilience—leading the path toward safer and more intelligent autonomous transportation in next-generation EVs [22].

Despite significant progress in multi-sensor fusion for obstacle detection, several challenges remain unresolved. Accurate calibration and temporal synchronization across heterogeneous sensors such as LiDAR, radar, and cameras continue to be a technical bottleneck, especially in dynamic operational environments where even minor misalignments can degrade detection accuracy. Real-time processing on embedded platforms is hindered by the high computational cost of deep learning models and the large data volumes generated by multi-modal sensing, often leading to latency that compromises safety. Long-range detection beyond 50 meters, critical for high-speed driving, remains difficult due to LiDAR's weather susceptibility and radar's lower spatial resolution. Furthermore, system cost and scalability are limited by the high price of mechanical LiDAR units and the complexity of multi-sensor integration, restricting deployment in mass-market EVs. Environmental robustness also requires improvement, as many existing systems experience substantial performance drops in heavy rain, fog, or snow, despite sensor redundancy. This review addresses these issues by synthesizing recent advances in AI-driven fusion frameworks, identifying effective strategies for adverse-weather resilience, evaluating hardware-accelerated solutions for edge deployment, and highlighting future research directions for robust, scalable, and cost-effective perception in next-generation AEVs.

This review offers several contributions that, to our knowledge, have not been presented together in prior literature. First, it provides the most comprehensive synthesis to date of AI-driven multi-sensor fusion techniques specifically targeted at real-time obstacle detection in AEVs, bridging both sensing hardware and deep learning–based processing frameworks. Second, it systematically compares data-, feature-, and decision-level fusion strategies, correlating their strengths and limitations with environmental conditions such as fog, rain, and low-light operation—an alignment rarely discussed in earlier surveys. Third, it incorporates an evaluation of hardware acceleration, model compression, and edge computing platforms to address the latency and resource constraints unique to EV embedded systems, an area often overlooked in prior reviews. Fourth, it identifies and categorizes open research problems—including long-range detection beyond 50 m, dynamic self-calibration, and cost reduction through solid-state sensors—while mapping these gaps to specific fusion and algorithmic solutions. Finally, the review proposes a forward-looking research agenda that integrates multimodal perception with V2X communication to extend situational awareness beyond line-of-sight, providing a roadmap for scalable, robust, and cost-effective deployment in next-generation AEVs.

3. SENSOR FUSION TECHNIQUES FOR OBSTACLE DETECTION

Sensor fusion is a technique that combines several sources of sensor information to provide a more accurate, complete, and reliable description of the environment around. In the context of obstacle detection for EVs, it combines data from various sources of sensors, such as LiDAR, radar, cameras, and thermal imaging systems. Its purpose is to enhance the accuracy, robustness, and resilience of perception, particularly in difficult driving environments such as poor visibility or adverse weather conditions [22].

3.1. Overview of sensor fusion

Sensor fusion techniques are generally classified into data-level fusion, feature-level fusion, and decision-level fusion depending upon when and in which manner the data from multiple sensors are combined [23], [24].

a. Data-level fusion

At the data level, the original raw data of all the sensors are fused before anything is processed. Data-level fusion has a low-level fusion which allows the system to get an overall sense of the environment. The largest advantage of data-level fusion is that it can use all the available sensor information without deleting early data and makes it such that the system is most accurate and comprehensive [24]. For instance, combining LiDAR point clouds, radar readings, and camera images in their raw states enables a system to achieve full contextual knowledge of the surroundings, such as object geometries, distances, and textures. This, however, involves an extensive computation and sophisticated algorithms to process and remove noise if there is any in the raw sensor data [25], [26].

b. Feature-level fusion

Feature-level fusion is the selection of specific features from the sensor data, for example, edges, shapes, texture, or motion patterns, before the fusion. Feature-level fusion is at a higher abstraction level than data-level fusion and generally results in lower computational complexity since the system operates on high-level features rather than raw data [26]. For example, LiDAR information can provide features such as surface shapes and object boundaries, while camera images can provide features such as object type (pedestrians, cars, and traffic signs). Radar may provide information related to object speed or direction. When these are combined, they create a more accurate portrayal of the environment that is easier to analyze and interpret [27].

c. Decision-level fusion

Decision-level fusion operates on the final output of multiple sensors and combines them into a single decision-making process. In obstacle detection, the system would use the obstacles detected and their locations from each sensor (LiDAR, radar, and camera) and combine these outputs to conclude about what obstacles are present in the environment [28]. Decision-level fusion is less computationally demanding than data-level and feature-level fusion, but may lose some valuable sensor data. Decision-level fusion, nonetheless, facilitates fusing the high-level decisions of a sensor or each sensor subsystem to form a robust result. For example, a radar sensor might detect an obstacle at a certain range, while a camera can help determine it to be a pedestrian or another vehicle. The fusion at the decision level would conclude that a pedestrian is in front of the vehicle [29]. Sensor types used for obstacle detection in fusion.

3.2. Principles and types of light detection and ranging

LiDAR is a time-of-flight (TOF) sensor technology. It transmits a laser pulse to an object and measures the time it takes for the pulse to return after hitting the object. This TOF is then utilized to calculate the distance of the object from the sensor, and this allows LiDAR to create high-resolution 3D point clouds of the scene. 3D point clouds become a critical factor in obstacle detection, object recognition, and scene perception for autonomous driving applications [29], [30]. One of the key advantages of LiDAR is that it has very high accuracy, and it can also perform well under varied lighting conditions. The illustration of the LiDAR principle is displayed in Figure 2.

Unlike cameras, which do not fare well in poor-light or night conditions, LiDAR does not get substantially impacted by the intensity of light and is hence an appropriate sensor to utilize under challenging environments like low-visibility conditions of fog, rain, or low-light conditions. Such a property renders it particularly worthwhile during night driving or during inclement weather [30]. LiDAR systems can be broadly categorized based on their scanning mechanism, which decides their performance, cost, and suitability for different applications. They are:

3.2.1. Mechanical light detection and ranging

The mechanical LiDAR units are the ancient technology used in most initial AV tests. They use a rotating laser beam to sweep across the full 360-degree field of view. They maintain a high-resolution, accurate 3D map of the surroundings and are therefore extremely accurate at mapping and object detection. However, the mechanical parts of rotating mechanical LiDAR add to the system's size, complexity, and wear over time. The mechanical parts and large size also result in higher production and maintenance costs [30].

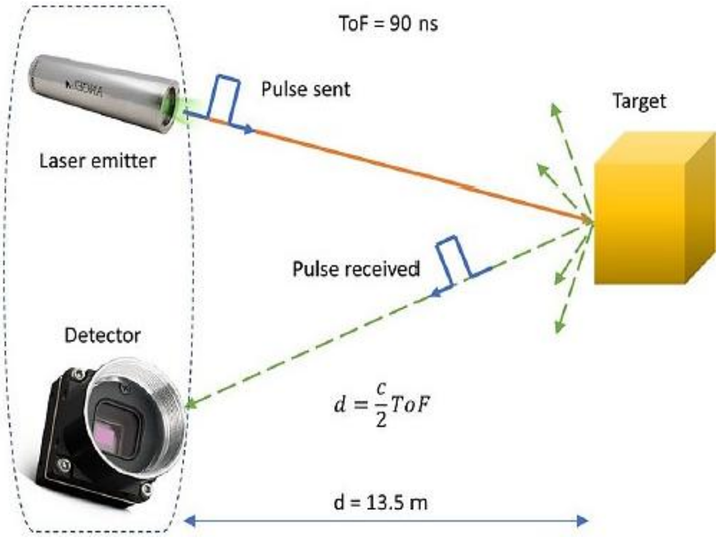

Figure 2. Illustration of LiDARs' principle

3.2.2. Solid-state light detection and ranging

Solid-state LiDAR systems utilize micro-electro-mechanical systems (MEMS) or optical phased arrays (OPA) to scan the surroundings without mechemical components. These systems are stronger, lighter, and more resistant to mechanical failure than mechanical counterparts. It is possible to make solid-state LiDAR compact, and this makes commercial application where weight, size, and cost considerations are paramount, the best to use. However, while the solid-state LiDAR comes with the advantage of compactness and durability, it does not provide as good resolution or distance as a mechanical LiDAR system. However, recent advances have significantly improved the performance of solid-state systems to the extent that they can be employed in high-end autonomous cars as well as consumer electronics [30], [31].

3.2.3. Flash light detection and ranging

Flash LiDAR systems record an entire scene in a single laser pulse, without the requirement for mechanical motion. Flash technology supports high frame rates and low motion artifacts, and it is ideal for use in high-speed applications where real-time processing is essential. Flash LiDAR is typically utilized in those cases where high field of view requirements exist, such as robotics or UAVs. Flash LiDAR can provide wide-angle, quick coverage but at the cost of resolution, potentially not providing such high-resolution point clouds as would be possible using mechanical or solid-state LiDAR [31].

3.3. Light detection and ranging in sensor fusion

While LiDAR alone is adequate to provide high-resolution 3D mapping of the surroundings, it can be enhanced when it is combined with other sensors like cameras, radar, and thermal imagers. Through multi-sensor data fusion, it is feasible to have better obstacle detection and scene comprehension through overcoming the inherent limitation of each of these sensors. For instance, cameras provide adequate color and texture information, useful for object recognition, but perform badly in poor light or weather. Radar performs optimally in low-visibility environments but lacks resolution to identify detailed object shapes. Thermal sensors perform well at identifying living obstructions such as pedestrians in the dark. By combining the capabilities of LiDAR with other sensors through sensor fusion techniques, systems can function better in a wider range of environmental conditions [31], [32].

3.4. Radar principle and types

Radar, which stands for radio detection and ranging, is used in obstacle avoidance for autonomous cars (AVs) in detecting, locating, and tracking objects via reflected signals using radio waves [33]. It is based on sending electromagnetic waves, usually microwave frequency (400 MHz to 40 GHz), and measuring the time delay, Doppler shift, and angle of arrival to calculate an object's range, velocity, and direction. The range is computed using (1):

$$R = \frac{C*t}{2} \quad (1)$$

Where the speed of light is represented by c and the round-trip time of the signal, while the Doppler effect enables velocity measurement by detecting frequency shifts in the reflected waves, crucial for dynamic environments like traffic [34].

Several radar types are employed in AVs: pulsed radar emits short, high-power pulses to measure range via TOF, with pulse-Doppler variants enhancing motion detection. There are several types of radar systems used in AVs, each suited for different aspects of detection:

3.4.1. Pulsed radar

Pulsed radar systems radiate short pulses of high-power electromagnetic energy and measure the TOF for the pulse after it reflects from an object. Based on TOF, such radars can calculate the range of objects. Pulsed radar systems are well suited for long-range detection, and pulse-Doppler types are also able to detect relative velocities of objects by calculating the frequency shift of the reflected signal [34]. This makes pulsed radar particularly suited for locating objects at some distance, particularly in the open. The working of LADAR is shown in Figures 3 and 4 explains about fundamental components of radar system.

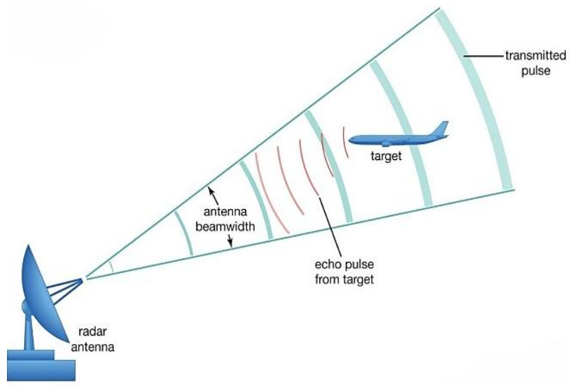

Figure 3. Working of LADAR

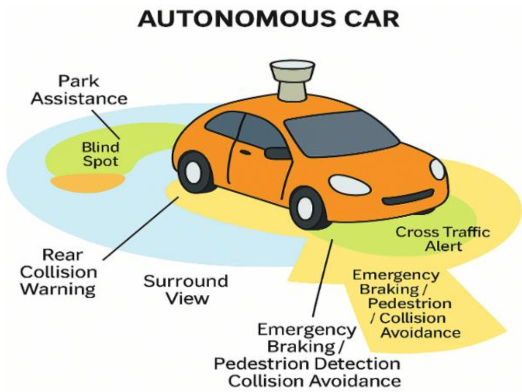

Figure 4. Fundamental components of a radar system

3.4.2. Continuous-wave radar

CW radar emits a steady signal that never takes the form of a pulse, and it is most appropriate for monitoring the speed of objects in motion. In contrast with pulsed radar, CW radar cannot directly gauge the range of an object but is highly capable of assessing the relative speed of objects. Because of this characteristic, CW radar finds optimal usage in environments where monitoring the movement of automobiles or other mobile barriers is imperative, as is often the case with high-traffic driving conditions [35]. The schematic diagram of radar system in shown in Figure 5.

Text frequency-modulated continuous-wave (FMCW) radar FMCW radar is popularly applied in the automotive field and takes advantage of both pulsed and CW radar. FMCW radars frequency modulate the continuous signal, hence enabling measurement of both range and velocity at the same time. FMCW radar can determine objects' speed and position through the analysis of the frequency shift (Doppler effect) and frequency modulation of the signal. These radars are comparatively small, low-power, and inexpensive, making them particularly suitable for short to medium-range detection in AVs, generally up to 200 m [35].

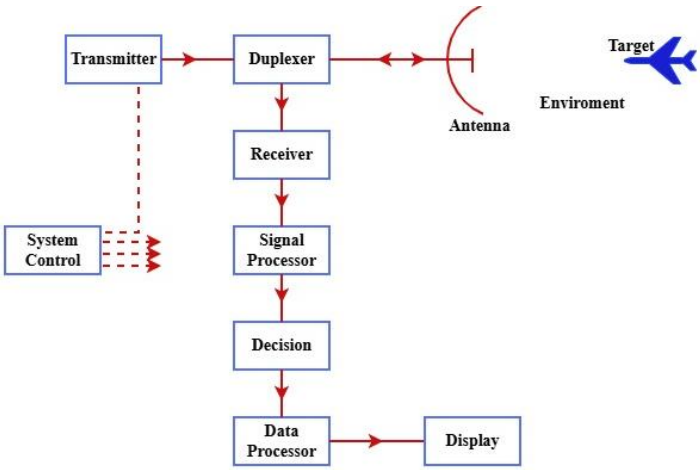

Figure 5. Radar system block diagram in schematic form

3.4.3. Synthetic aperture radar

Synthetic aperture radar (SAR) is a radar method that employs the motion of the radar platform (e.g., an aircraft or a satellite) to form high-resolution images of the viewed area. Although SAR is mostly employed for cartography and terrain mapping and less for real-time obstacle detection, its high-resolution imaging nature places it adequately for environmental mapping and monitoring. SAR systems offer high-resolution images of the environment, which can be applied for creating maps or in cases of requiring detailed topography [36].

3.4.4. Bistatic/multistate radar

Bistatic radar systems have distinct transmitter and receiver locations to provide greater flexibility in the radar system architecture and improved detection in clutter or highly dynamic situations. Multistate radar employing many transmitters and receivers has the potential to provide greater overall coverage and to improve object detection in heavy interference environments, for example, heavy urban environments. The systems find most application in difficult environments where standard monostatic radar performance may be hindered [36].

Radar’s penetration capability through inclement weather like rain, fog, and snow are among its key strengths over LiDAR, which struggles in these environments. Since radar can offer accurate range and velocity data under poor weather, it is counted as a complementary sensor to LiDAR, cameras, and other sensors in self-driving cars. But the comparatively low resolution of radar makes it difficult to separate objects with high detail. To overcome this shortcoming, radar data is usually processed in conjunction with other sensor data using sensor fusion methods, enhancing the overall classification accuracy and object detection capability [37].

3.5. Thermal sensor principle and types

Thermal sensors, or infrared (IR) sensors, are vital to AV obstacle detection systems under poor circumstances of visibility like fog, smoke, rain, or night. The sensors detect infrared radiation emitted by objects naturally due to their temperature, allowing them to detect the environment passively without illumination by external light sources [38]. The principle behind thermal imaging is that all objects above absolute zero give off infrared radiation. To create thermal images, this radiation is detected and transformed into electrical signals. Thermal images represent temperature variations in the scene and are effective in the detection of pedestrians, animals, and heated parts of the vehicle, which may not be observable by visible-light cameras or LiDAR technology [38], [39]. The illustration of thermal sensor is shown in Figure 6.

There are two large categories of thermal sensors:

a. Uncooled thermal sensors

They are most widely utilized for AV purposes. They are at room temperature and have materials such as vanadium oxide or amorphous silicon. They are inexpensive, compact, and provide adequate sensitivity for short- to medium-range uses (100 m), for example, pedestrian detection [39].

b. Cooled thermal sensors

These are finer and can sense smaller temperature gradients. They employ cryogenic cooling to minimize sensor noise and come in high-end applications with large range detection and high resolution. They are bigger and pricier, but less prevalent in vehicle systems [39].

Thermal sensors are commonly combined with radar and visible-light cameras to overcome constraints such as low spatial resolution and enhance detection performance in real-world driving environments. Multimodal sensor fusion enables AVs to perceive their environment consistently under various unfavorable conditions [40], [41].

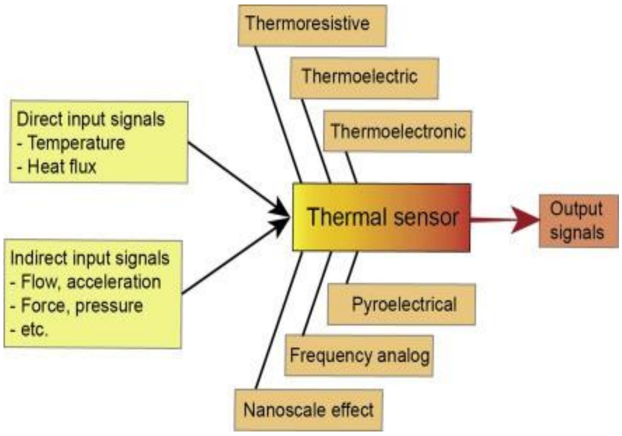

Figure 6. Illustration of thermal sensor principle

3.6. Light detection and ranging and vision sensors

LiDAR and vision sensors are fundamental technologies of current obstacle detection and environment perception solutions, especially in applications such as intelligent surveillance, robotics, and AVs. LiDAR sensors emit laser pulses and record the time taken by the reflected light to come back, producing precise 3D point clouds of the environment [41]. LiDAR sensors are known for high spatial accuracy, long-range measurement, and durability in low-light or night conditions. For example, LiDAR sensors such as the Velodyne VLP-16 or RPLiDAR A1 can detect full 360-degree surroundings in real-time and offer high-accuracy spatial perception [42]. Yet, there are some limitations of LiDAR, i.e., a high price tag, vulnerability to bad weather conditions, e.g., fog and heavy rain, and relatively low resolution in comparison with optical cameras. In addition, the point cloud data obtained by LiDAR demands the use of high computer capacity for analysis and interpretation [43].

In the mentioned figure, the left image displays a front view from an RGB camera capturing the visual appearance of cars and objects in an urban setting. The 3D point cloud output from a LiDAR sensor is displayed in the right image, giving depth and spatial information of objects such as cars and road features detected. To refer to sensor fusion, object detection algorithms, or real-time processing [43]. Vision sensors, nonetheless, sense rich contextual and semantic information in high-resolution images. Vision sensors can sense object features like color, texture, and shape, all of which are important for object recognition and classification [44]. With developments in deep learning, vision-based systems employ CNNs and real-time models like YOLOv5 and MobileNetV3 for object tracking as well as detecting a wide range of objects like cars, pedestrians, and road signs [44]. Vision sensors are very light-sensitive and may break down in situations like glare, night, rain, or fog. In contrast to LiDAR, monocular vision systems do not have intrinsic depth information unless augmented with stereo vision or depth estimation methods [45]. The comparison of vision-based and LiDAR-based obstacle detection is shown in Figure 7.

Figure 7. Comparison of vision-based and LiDAR-based obstacle detection in urban driving scenario

As a way of improving perception capabilities and overcoming shortcomings of single sensors, sensor fusion methods gain more popularity. By fusing LiDAR's geometric precision with vision data's semantic depth, fusion systems can deliver more robust and assertive environmental awareness [46]. One could do sensor fusion at the raw data, feature, or decision levels, which provides a compromise in terms of complexity and real-time performance [46]. Such combined systems that use both LiDAR and vision work better than standalone systems on tasks such as semantic segmentation, object classification, and obstacle detection in challenging situations such as low light or dense urban environments [47]. For redundancy and fail-safety in mission-critical tasks such as autonomous driving, multi-modal systems are also necessary [48].

4. LIDAR AND ULTRASONIC SENSORS

Because their detecting modes are complementary, LiDAR and ultrasonic sensors are often employed in autonomous systems for obstacle detection. To build high-resolution 3D point clouds reflecting the spatial geometry of the environment, LiDAR sensors emit laser pulses and measure how long it takes for the light to bounce back [48]. LiDAR is highly accurate and far-range detection, a few meters to more than 200 meters in range depending on the model, and therefore well-suited to the outdoors and high-speed applications such as drones and AVs [48]. LiDAR devices are comparatively costly and prone to environmental conditions like fog, heavy rainfall, and dust particles which scatter or absorb the laser beams and decrease detection dependability [49]. Furthermore, LiDAR produces enormous volumes of data, which requires enormous processing capacity in real-time applications. Conversely, ultrasonic sensors emit high-frequency sound waves, which then detect the time taken for the wave to bounce back after hitting an object [49]. The sensors are simple to implement, low-cost, and suitable for object detection in short ranges, usually up to 2–5 meters. They are used in low-speed applications like parking assist systems, robot vacuum cleaners, and indoor mobile robots. Ultrasonic sensors are not very sensitive to lighting levels and thus best utilized in dark situations. They have disadvantages such as poor spatial resolution, narrow beam angles, and ambient noise or interference by sloping or soft surfaces which lack the capability of reflecting sound waves properly [49], [50].

For addressing the limitation of each single sensor, latest obstacle detection systems frequently make use of LiDAR as well as ultrasonic sensors together. By sensor fusion, LiDAR high-definition long-range perception and reliable close-range perception using ultrasonic sensors are realized, improving overall perception ability and redundancy of the system [50]. For instance, LiDAR in self-driving cars can be used for real-time mapping and object detection for traffic situations and ultrasonic sensors can be applied for low-speed operations like parking or detection of obstacles in narrow spaces [50]. These hybrid sensing platforms offer a stable and low-cost sensing solution for environment perception in general indoor and outdoor environments [50], [51].

5. LIDAR AND THERMAL SENSORS

LiDAR and thermal cameras are increasingly featured in sensor fusion applications to maximize the performance of obstacle detection, particularly in autonomous applications and safety-critical contexts like drones, EVs, and surveillance. LiDAR generates detailed 3D point clouds of the environment by emitting laser pulses and measuring how long it takes for the light to bounce back after it hits an object [51]. LiDAR sensors have the capacity to provide true distance readings, high field-of-view, as well as function under variable illumination conditions and therefore are suited to outdoor navigation and mapping [51]. However, their use is hindered when there is undesirable weather like heavy rain, fog, and snow, whereby the laser beam can be scattered or absorbed [52]. Also, LiDAR lacks the ability to detect temperature variation or thermal signature of an object, significant in conditions of low visibility.

Thermal sensors, such as infrared thermographic cameras like the AMG8833 or FLIR Lepton, sense infrared radiation from objects and transform it into thermal images or temperature maps. Thermal sensors are able to detect in complete darkness and are also not affected by light conditions and are thus of unparalleled utility at night and under low-visibility conditions [52]. Thermal cameras are very good at detecting living objects like human and animals based on their heat signature, even if the visual or LiDAR information might be obstructed. Thermal cameras have worse spatial resolution than RGB sensors or LiDAR, and cannot offer accurate geometric or range information [52]. Combining LiDAR and thermal sensors into a common perception system overcomes the limitations of each sensor technology while exploiting their strengths. The geometric precision of LiDAR is complemented by the heat-based visibility of thermal sensors to facilitate correct object detection in dynamic environmental conditions such as fog, dust, darkness, and complex backgrounds. The combined LiDAR and thermal camera sensors for understanding the 3D scenes are shown in Figure 8.

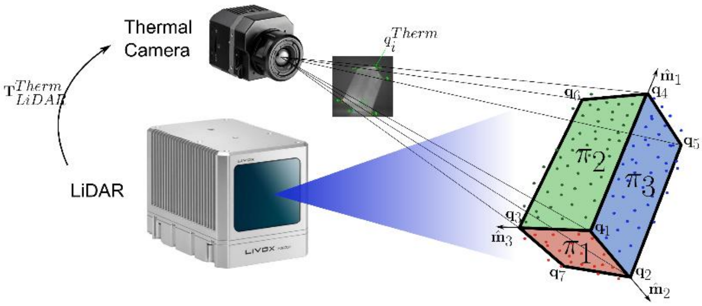

Figure 8. Combining LiDAR and thermal camera sensors to understand 3D scenes

LiDAR point cloud information and thermal images can be fused by sensor fusion algorithms at the raw data, feature, or decision level to enhance item classification, anomaly detection, and scene understanding [53]. Safety-critical use cases like autonomous driving in adverse weather and surveillance in low-light or ambiguous conditions are increasingly depending on multi-modal systems.

6. LIDAR AND RADAR

LiDAR and radar sensors both find key applications in autonomous systems for effective environment perception and hazard detection. LiDAR works based on the principle of lighting up the environment with laser beams and measuring the time taken by the reflected light to come back, which generates precise three-dimensional point clouds of the surrounding environment [53]. These sensors have high spatial resolution and accuracy, which are particularly beneficial in accurate mapping, localization, and robot, drone, and AV obstacle detection [54]. LiDAR is particularly suited for applications where a high-resolution reconstruction of the surface is needed, such as urban navigation or autonomous driving. Yet, LiDAR is weather dependent in heavy rain, fog, and snow, causing laser beams to scatter and diminishing the precision of measurement [54]. Heavy computation expense and LiDAR point cloud data processing are also issues that must be overcome in order to employ it on a large scale.

The sensor fusion coverage using LiDAR and radar in ADAS-equipped vehicles is shown in Figure 9. On the other hand, radar uses electromagnetic waves in the radio frequency range to identify objects and determine their angular location, speed, and distance [55]. Radar has good object detection at long range and some today can detect objects 200 m or more. Radar excels in its resistance to bad weather and long-range sensing but tends to have poorer resolution than LiDAR and is not capable of providing the same level of high detail 3D information. The radar point cloud is generally coarser, and object classification and identification are harder without additional processing [55]. In applications like adaptive cruise control in driverless cars, traffic surveillance, and collision avoidance, radar's capacity to measure an object's speed and velocity remains a unique advantage.

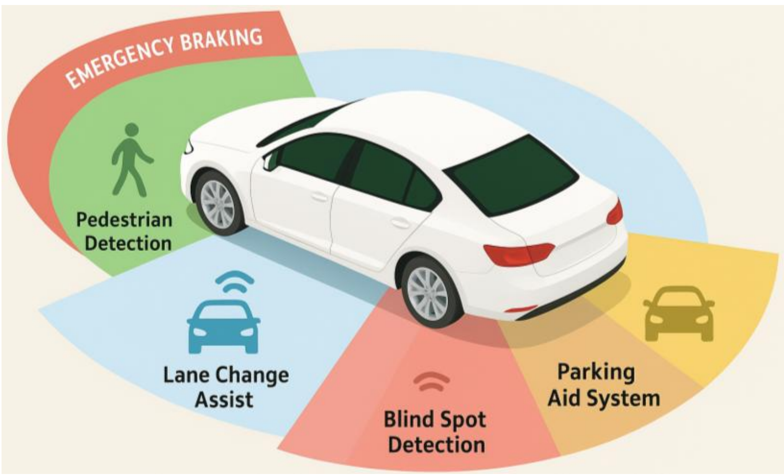

Figure 9. Sensor fusion coverage using LiDAR and radar in ADAS-equipped vehicles

The coordinate system for radar camera fusion is shown in Figure 10. Integration of LiDAR and radar sensors has become an accepted remedy to the vulnerabilities of each sensor technology. Combining LiDAR's precise 3D information at high resolution with radar's capability to operate in poor weather conditions leads to more accurate and trustworthy detection of obstacles even in poor environments [56]. Sensor fusion methods tend to operate at various levels—decision, feature, or raw data fusion—based on the application and the required level of accuracy-computational efficiency trade-off [57]. For instance, in AVs, LiDAR may be used to map and recognize static objects and features, and radar excels at detecting objects in motion, such as other vehicles or pedestrians, in complex driving scenarios [57]. The sensors together provide complementary information that enhances system-level reliability, safety, and responsiveness in real-time.

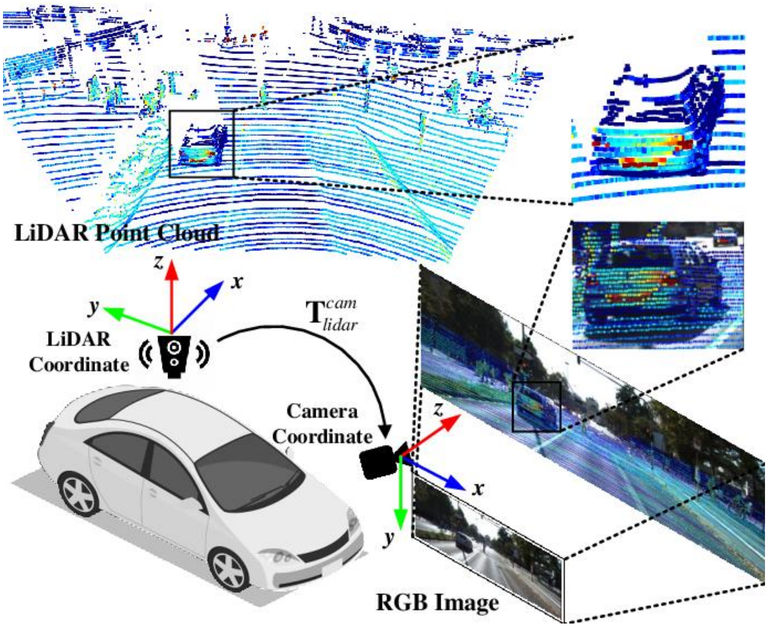

Figure 10. Coordinate system for radar-camera fusion

7. MERGING MILLIMETER WAVE RADAR AND CAMERA

Millimeter wave radar at the frequency range 30–100 GHz is capable of detecting direction and distance of the target with high weather robustness but with poor resolution and bad non-metallic target recognition [58]. Cameras, though economical, are not stable in harsh conditions [58]. Data-level, feature-level, and target-level are some of the techniques for fusion. Data-level fusion employs calibration to register radar point clouds with picture pixels but suffers with radar's sparse data. Feature-level fusion lightens computation by projecting radar targets onto images to define regions of interest [59]. In their evaluation of mmWave radar-vision fusion highlighted how effective it performs in rain and fog. A resilient radar-camera hybrid framework for object detection and range estimation was proposed by emphasizing real-time performance utilized shallow neural networks for radar-based vulnerable road user detection. Target-level fusion, though it includes detection results, suffers from the limitations in monocular camera depth [60]. It is important to coordinate time and space with timestamps and calibration [60], [61].

8. LIDAR AND INFRARED

LiDAR and infrared sensors are essential technologies for enriching obstacle detection in autonomous systems, providing complementary information to complement environmental perception. LiDAR operates on the principle of sending laser pulses and measuring the time taken by the sensor to capture reflected light, generating high-resolution 3D point clouds to facilitate accurate mapping and localization of the surrounding environment [61]. The accuracy of LiDAR and high sensitivity in measuring distance with precise accuracy render it an indispensable tool for applications in AVs, robots, and unmanned aerial systems (UAS) [62]. Rain, fog, and other meteorological factors may interfere with LiDAR and snow because the conditions will absorb or scatter the laser pulses, which may create blind spots or inaccurate detection [63]. Furthermore, LiDAR's steep cost and big data handling requirements are issues that may limit its scalability for certain applications.

Infrared detectors, including thermal cameras and passive infrared (PIR) detectors, detect the radiation of heat from objects so that they are able to work effectively under low-visibility conditions such as darkness or fog.

Thermal infrared sensors can pick up the temperature variations between objects, making it possible for living organisms (e.g., human beings and animals) to be identified by their heat signatures, even when they may not be able to observe or utilize LiDAR information effectively [63]. Because infrared sensors are not affected by lighting conditions like visible cameras, they are also suitable for use at night [64]. However, thermal sensors generally have lower spatial resolution than LiDAR and are less suitable for capturing precise 3D information about the environment, which could be disadvantageous for high-detail mapping and obstacle avoidance tasks [65]. The integration of LiDAR and infrared sensors takes advantage of both technologies to create an enhanced and richer perception system.

LiDAR’s ability to generate high-resolution 3D point clouds can be combined with infrared thermal data to enhance obstacle detection in cluttered environments, for example, in low-light, fog, or crowded conditions [65]. For example, LiDAR can be used for spatial mapping, while thermal sensors can be used to identify living organisms or differentiate between objects with similar structure but different thermal signatures. Sensor fusion algorithms at the raw data, feature, or decision level allow combining the spatial precision of LiDAR with infrared sensor thermal sensitivity to improve detection accuracy, object classification, and environmental perception [65]. This combined method is of immense application in autonomous driving, search-and-rescue missions, and surveillance missions, where spatial precision and thermal discrimination are of utmost importance to provide safety and performance [66].

9. OBSTACLE AVOIDANCE ALGORITHMS

Obstacle avoidance algorithms enable autonomous robots, drones, and vehicles to navigate safely by detecting and evading obstacles in real time. These algorithms process sensor data from LiDAR, radar, cameras, and ultrasonic sensors to generate collision-free paths, ensuring safety and reliability in dynamic and unstructured environments [66], [67]. Broadly, obstacle avoidance methods can be categorized into six groups: reactive, deliberative, hybrid, model predictive control (MPC), machine learning (ML)-based algorithms, and sensor-fusion-based methods.

9.1. Reactive algorithms

Reactive algorithms rely solely on real-time sensor observations, without a pre-built map. Techniques such as the vector field histogram (VFH) and dynamic window approach (DWA) are widely used due to their computational efficiency. However, they struggle in complex environments because they lack global planning capability [67].

9.2. Deliberative algorithms

Deliberative methods use an internal map to compute optimal, collision-free paths. Algorithms like A* and Dijkstra’s are commonly employed but require accurate maps and high computational resources, making them unsuitable for real-time autonomous navigation in dynamic environments [68].

9.3. Hybrid algorithms

Hybrid approaches integrate reactive and deliberative strategies to balance real-time responsiveness with global planning. The timed elastic band (TEB) method, for example, combines local obstacle avoidance with global trajectory optimization and is widely used for mobile robots in cluttered environments [68], [69].

9.4. Model predictive control

MPC-based controllers predict future system states and optimize control inputs to avoid obstacles dynamically. They are particularly suitable for high-speed autonomous platforms, such as UAVs, where anticipating obstacle motion is essential for safe navigation [70].

9.5. Machine learning-based algorithms (overview)

ML approaches enable autonomous systems to learn from data and adapt to complex, unstructured environments. These methods are especially effective in urban driving or variable weather conditions, where traditional rule-based algorithms perform poorly. ML models can classify objects, predict obstacle trajectories, and support decision-making for navigation [70].

9.6. Sensor fusion-based algorithms

Sensor fusion algorithms combine complementary data from multiple sensors—such as LiDAR, radar, and cameras—to improve perception accuracy. Fusion enhances reliability in adverse weather conditions and reduces the limitations of individual sensors. Modern autonomous systems often integrate fusion with ML techniques for improved robustness [71], [72].

9.7. Representative learning-based obstacle detection algorithms

To maintain structural consistency, specific ML algorithms used for obstacle detection are grouped under this unified subsection.

9.7.1. You only look once

YOLO is a state-of-the-art deep learning framework for real-time object detection. By treating detection as a single regression problem, YOLO divides an image into grids and predicts bounding boxes and class probabilities in one forward pass through a CNN. This design enables high frame rates (30–60 FPS), making YOLO suitable for AV pedestrian detection, drone navigation, and real-time robotics [72], [73]. The YOLO object detection system is shown in Figure 11.

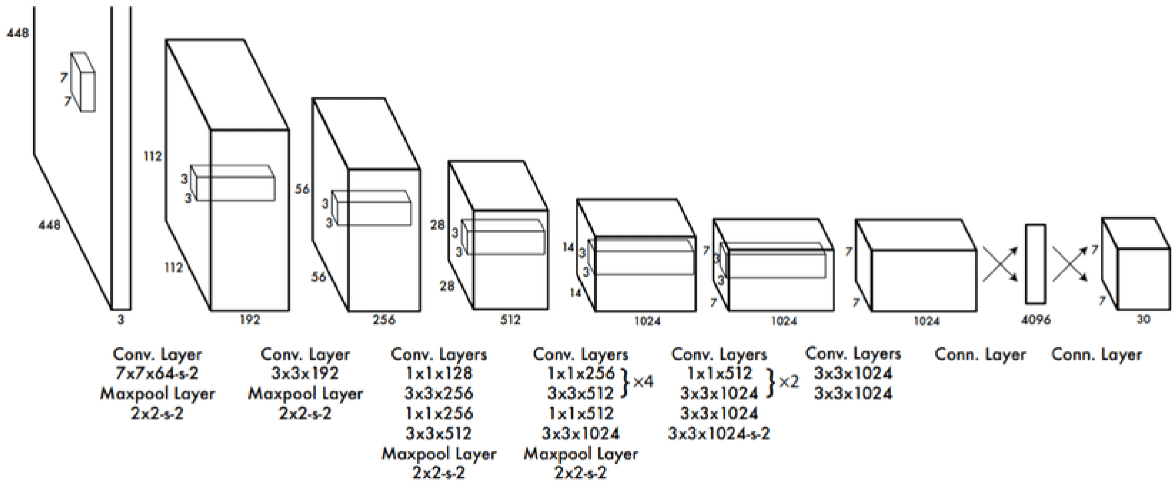

Figure 11. YOLO object detection

YOLO’s architecture includes: i) backbone: feature extraction (e.g., Darknet and CSP-Darknet), ii) neck: feature aggregation (e.g., PANet); and iii) head: bounding box and class prediction.

Recent YOLO versions (YOLOv4 and YOLOv5) incorporate innovations such as mosaic augmentation, anchor-free detection, and network scaling to improve speed and accuracy [73], [74]. YOLO is often fused with LiDAR or radar for depth-aware detection. LiDAR-camera projection improves distance estimation, while radar provides motion cues that enhance detection under fog, rain, or low-light conditions [75].

9.7.2. Random forest

Random forest (RF) is a classical ensemble ML algorithm used for obstacle classification in scenarios where computational resources are limited. By combining multiple decision trees trained on random feature subsets, RF offers robustness against noise and missing data. It has been applied to classify LiDAR clusters, radar signatures, and thermal images for obstacle detection in robots and AVs [75]–[77]. The workflow of RF is shown in the Figure 12.

RF is favoured for: low computational cost, robustness to noisy inputs, and interpretability. But may underperform deep learning models in complex urban scenes. RF is often paired with sensor fusion to enhance classification reliability in adverse conditions [77].

9.8. Deep learning and multimodal fusion techniques

ML techniques—particularly deep learning—have significantly advanced obstacle detection by enabling autonomous systems to learn hierarchical features and adapt to dynamic scenes. Figure 13 presents the general ML workflow.

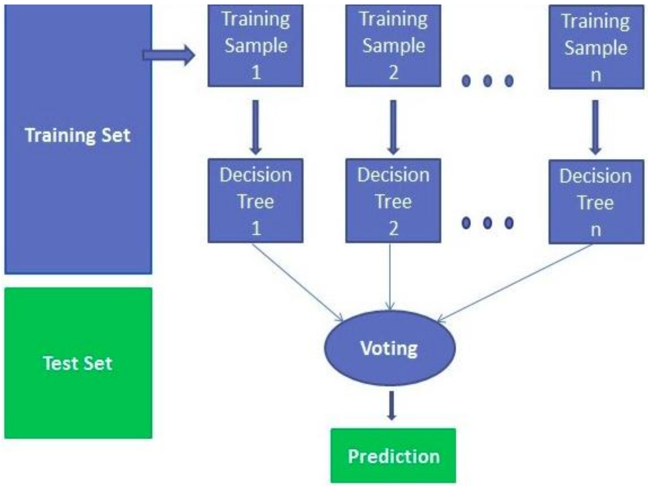

Figure 12. Working of RF

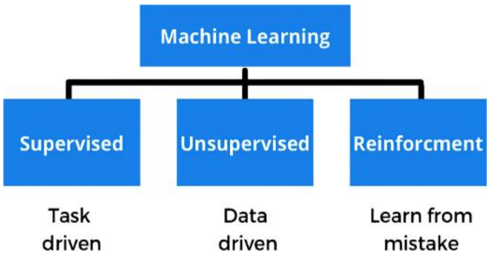

Figure 13. ML block diagram

9.8.1. Artificial neural network

Artificial neural networks (ANNs) process sensor features through interconnected neuron layers, learning object categories such as pedestrians and vehicles using camera images or LiDAR features. Their flexibility enables use across multiple modalities, although they require large datasets and computation for training [77].

9.8.2. Convolutional neural network

CNNs extract hierarchical image features for tasks such as pedestrian detection, road sign classification, and semantic segmentation. Architectures like faster R-CNN and SSD have been widely deployed in AV perception. CNNs also complement LiDAR by providing semantic context that improves 3D detection accuracy [78].

9.8.3. Recurrent neural network and long short term memory models

Recurrent neural networks (RNNs)—and especially long short term memory (LSTM) networks—are effective for temporal prediction tasks, such as forecasting pedestrian trajectories or vehicle movement. Their memory mechanism enables modeling of sequential motion patterns, supporting proactive obstacle avoidance [78], [79].

9.8.4. Deep neural networks for 3D perception

Deep neural networks (DNNs)-based architectures such as PointNet++, VoxelNet, and BEV-based detectors learn high-level 3D features from LiDAR data. These networks excel in cluttered or partially occluded environments but are computationally intensive [79], [80].

9.8.5. Generative adversarial network

Generative adversarial networks (GANs) are used to synthesize adverse-weather or rare training scenarios, enabling models to generalize better to fog, rain, and night conditions. This improves ML-based obstacle detection robustness in real-world deployments.

9.8.6. Multimodal fusion frameworks

Fusion frameworks combine LiDAR geometry, radar velocity, and camera semantics to achieve reliable obstacle detection under diverse conditions. Recent work [81], [82] proposes end-to-end deep fusion networks integrating all three modalities for enhanced detection accuracy. Advanced techniques such as probabilistic occupancy grids and joint radar-camera-LiDAR calibration further improve obstacle tracking and segmentation performance [83], [84].

Deep learning and fusion remain central to state-of-the-art obstacle avoidance, although challenges persist in real-time computation, cross-sensor heterogeneity, and generalization to unseen environments [85]–[87].

9.9. Performance metrics

Experimental evaluation considered detection distance, drone speed, and separation distance from both static and moving obstacles.

- For static obstacles, detection distance decreased with increasing flight speed, yielding a maximum safe speed of 0.6 m/s.
- For dynamic obstacles, a safe operating speed of 0.35 m/s was required, indicating tighter reaction time constraints.

10. SENSOR FUSION CHALLENGES AND SOLUTIONS IN OBSTACLE DETECTION FOR EV

Sensor fusion plays a critical role in enhancing the perception capabilities of EVs, especially for real-time obstacle detection in dynamic environments. However, integrating data from heterogeneous sensors—such as LiDAR, radar, and cameras proposes significant challenges related to calibration, uncertainty, computational complexity, and environmental robustness. This section provides an in-depth discussion of these challenges and explores state-of-the-art solutions.

10.1. Sensor calibration and alignment

Accurate sensor calibration and alignment are fundamental to successful sensor fusion. Each sensor has a distinct coordinate system and data format. Aligning them in a unified reference frame is vital for coherent data interpretation. The sensor installation positions are shown in Figure 14.

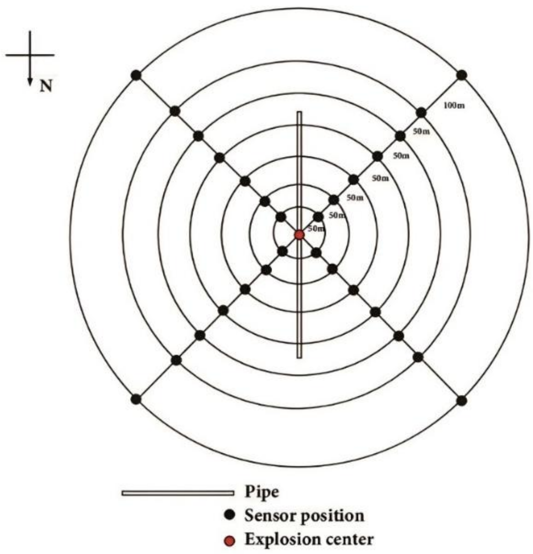

Figure 14. Schematic diagram of sensor installation positions

10.1.1. Light detection and ranging and camera calibration

LiDAR supplies 3D spatial information, while cameras supply rich visual texture in 2D. Calibration usually entails estimation of the transformation matrix (rotation and translation) between the camera and LiDAR coordinate frames. Checkerboard calibration, maximization of mutual information, and deep learning-based registration are utilized.

10.1.2. Radar calibration

Radar sensors, while being resistant to poor weather, provide lower resolution. Radar calibration against LiDAR and cameras typically consists of aligning reflectivity peaks or referencing landmarks.

10.1.3. Temporal synchronization

Sensors have varying frequencies and latencies. Time synchronization is required to prevent spatial-temporal drift, utilizing hardware times-tamping or software interpolation. Sophisticated calibration schemes, including target-less calibration based on semantic segmentation and point cloud alignment, have been developed to carry out this operation automatically.

10.2. Sensor data noise and uncertainty

Sensor readings naturally come with noise, distortion, and uncertainty, which can severely affect the performance of obstacle detection.

a. Light detection and ranging

Rain, fog, or snow causes performance to degrade through light absorption and scattering. Ghost points or incomplete scans can be caused by reflective or transparent surfaces.

b. Radar

Although more resilient in extreme weather, radar is plagued by low angular resolution, multipath reflections, and Doppler ambiguity.

c. Cameras

Cameras are photoreactive, glare-sensitive, motion blur-prone, and subject to occlusion. Performance can be drastically impaired under low-light or nighttime conditions.

d. Probabilistic filtering

Bayesian filters like Kalman filters, particle filters, and unscented Kalman filters (UKF) assist in approximating the state of moving obstacles.

e. Denoising using deep learning

Neural networks such as denoising convolutional neural network (DnCNN) and U-Net are employed to remove noise from depth maps and restore lost features.

f. Uncertainty modeling

Monte Carlo dropout and Bayesian neural networks estimate the confidence of predictions to prevent false positives. Sensor fusion assists in covering the limitations of single modalities by cross-validating data and supporting robust detections.

10.3. Requirements for real-time processing

LiDAR high-frequency data (e.g., 10–20 Hz), camera (e.g., 30–60 fps), and radar need to be processed and fused in real time, and there are challenges with computation load, memory, and latency.

a. Data volume

One LiDAR scan can have more than 100,000 points; camera frames are high-res images; and radar returns numerous signal reflections.

b. Latency sensitivity

Latency in fusion and object recognition will result in decision-making failure, compromising road safety.

c. Resource constraints

EV embedded systems tend to have less processing power than data center environments.

d. Edge computing

The NVIDIA Jetson Xavier, Google Coral, and Intel Movida's platforms provide parallel processing for deep learning inference on the edge.

e. Model optimization

Methods like quantization, pruning, and tensor decomposition minimize model size and inference latency without compromising accuracy.

f. Fusion frameworks

Modular frameworks like ROS, Apollo, and Autocare utilize multi-threaded data pipelines to fuse sensors in real-time. Future solutions might also utilize neuromorphic hardware and event-based cameras for yet lower-latency processing.

11. RELATED WORK

11.1. Vision-based safety systems

Vision-based systems are extensively employed for obstacle detection owing to their cost-effectiveness and potential for customization. Fawole and Rawat [88] discussed their applications in HMC, such as collision avoidance and safety zone monitoring. Deep learning techniques, i.e., CNNs and GANs, improve monocular depth estimation for navigation. Thottempudi *et al.* [89] utilized MiDaS for drone navigation in indoor settings.

11.2. Multi-sensor fusion

In inclement weather, multi-sensor fusion of LiDAR, radar, and cameras improve detection accuracy. Used DNNs to combine radar, LiDAR, and cameras. Recommended the integration of radar and LiDAR for powerful obstacle detection. These methods suggest combining LiDAR and vision for drones and electric cars [90]. The table shows the summary of a few recent publications reviewed on AVs, which fuse LiDAR and at least one other type of sensor for obstacle avoidance, sorted by operating environment, type of vehicle, LiDAR type and brand, secondary sensor, main objective of the sensor fusion, and obstacle avoidance algorithm used. Table 2 enhances the comparision of existing work to different types of systems.

Table 2. Summary of existing work comparison with different types of systems

Environment	Type of vehicle	LiDAR type	Vision	Sonar	Radar
Outdoors	USV	3D	✓		
Outdoors	AC	3D	✓	✓	✓
Indoors	AMR	2D	✓		
Outdoors	AMR	2D	✓	✓	
Indoors	AMR	2D	✓		
Indoors	AMR	2D	✓		
Outdoors	AC	3D	✓		✓
Indoors	AMR	2D	✓		
Indoors	AMR	2D	✓	✓	
Indoors	AMR	2D	✓		
Outdoors	AMR	2D	✓	✓	

12. ANALYSIS AND POTENTIAL RESEARCH DIRECTIONS

A review of 52 publications from 2020 to 2025 on obstacle detection in EVs using LiDAR and radar sensor fusion provides insights into current trends across autonomous cars, mobile robots, drones, and water/ground-based systems. The analysis highlights sensor adoption, vehicle types, operating environments, LiDAR variants, and primary objectives, reflecting the rapid evolution of multi-sensor fusion technologies. In sensor adoption, 3D LiDAR dominates, employed in 63.5% of systems due to its high-density point clouds and 360° field of view, making it ideal for complex environments. Radar, particularly 24–77 GHz imaging radar, is used in 51.9% of fusion setups, valued for its robustness in adverse conditions. Vision cameras and thermal imaging complement LiDAR in 69.2% and 40.3% of studies, respectively, enhancing detection in low-light or harsh weather scenarios. Autonomous electric cars (AECs) lead vehicle applications, comprising 57.7% of implementations, driven by demand for level 2–4 autonomy in passenger vehicles.

Autonomous mobile robots (AMRs) account for 21.2%, primarily in indoor industrial settings, while UAVs, UGVs, and USVs constitute 21.1%, focusing on specialized tasks like surveillance. Outdoor environments, including urban, off-road, and highway scenarios, dominate 76.9% of studies, whereas 23.1% target indoor or constrained spaces, such as warehouses and last-mile delivery systems.

LiDAR type usage varies by application: 3D LiDAR is prevalent in 68.2% of outdoor studies, supporting high-speed and dynamic obstacle detection, while 2D LiDAR is used in 78.4% of indoor studies for planar navigation. 1D LiDAR, found in 9.6% of cases, supports edge-based systems like brake assist in drones or EVs. The primary focus of these studies is obstacle detection and classification (94.2%), with navigation and simultaneous localization and mapping (SLAM) integrated in 46.1% of cases to enable autonomous path planning. Terrain and surface condition mapping, often leveraging thermal and radar data, appears in 21.1% of systems, particularly for off-road or challenging environments.

The Figure 15, stating that it illustrates the number of publications against the types of secondary sensors used for fusion with LiDAR, highlighting trends in sensor adoption within recent literature. Similarly, Figure 16 is now introduced as showing the number of publications categorized by the primary objectives of sensor fusion, which provides context for understanding the research priorities and application focus in the field. These additions ensure that each figure is properly cited, contextualized, and directly connected to the discussion in the main text, improving readability and adherence to publication guidelines. These trends underscore the critical role of multi-sensor fusion in advancing EV autonomy while highlighting the need for continued innovation to address environmental and computational challenges.

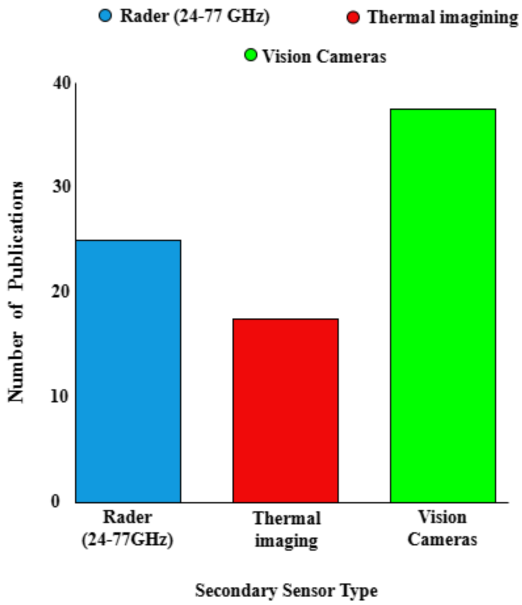

Figure 15. No. of publications against types of secondary sensors used for fusion with LiDAR

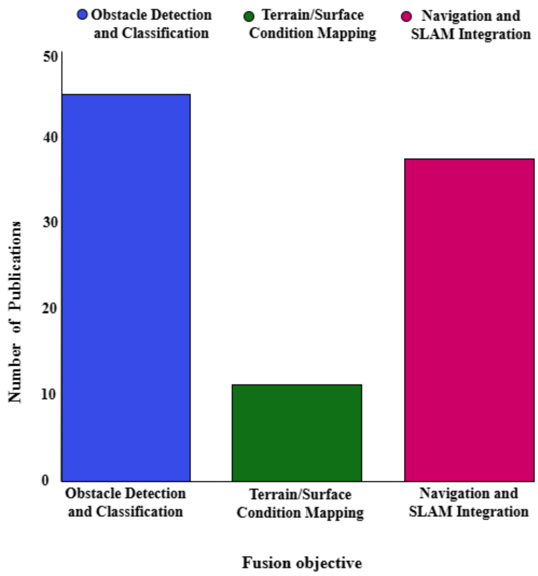

Figure 16. No. of publications against sensor fusion objective

The synthesis of literature in this review reveals that while multi-sensor fusion significantly enhances obstacle detection performance, the choice of fusion strategy and sensor combination must be tailored to operational requirements and constraints. Data-level fusion offers the richest information but demands high computational resources, making it suitable primarily for research and high-end platforms, whereas feature- and decision-level fusion provide better scalability for real-time embedded deployment. LiDAR–radar combinations consistently outperform single-sensor setups in adverse weather, while the inclusion of thermal imaging is particularly beneficial for low-light pedestrian detection. Deep learning architectures such as YOLOv5 and PointPillars have proven effective for real-time processing, but their computational demands necessitate model compression and hardware acceleration for in-vehicle applications. The findings suggest that future research should prioritize adaptive, context-aware fusion systems that dynamically select the optimal sensor subset and processing pipeline based on environmental conditions and mission priorities. Additionally, the integration of multi-modal fusion with V2X communication could extend perception beyond line-of-sight, addressing occlusion and range limitations. Standardized benchmark datasets covering diverse weather and lighting conditions will be critical for fair comparison and reproducibility, while advancements in low-cost solid-state LiDAR and high-resolution imaging radar will make robust fusion systems more accessible for mass-market EVs. By aligning sensor fusion research with these technological and infrastructural trends, the field can move toward scalable, reliable, and context-aware obstacle detection for next-generation autonomous transportation.

12.1. Potential

To advance obstacle detection in EVs beyond 2025, to overcome present constraints and improve system performance, several research avenues are suggested. These focus on improving robustness, efficiency, range, affordability, intelligence, and connectivity in multi-sensor fusion systems, particularly those leveraging LiDAR and radar. A critical challenge is the reduced performance of LiDAR-based systems in adverse weather, with 58% experiencing degradation in fog, snow, or rain. Integrating thermal imaging with mmWave radar can ensure reliable obstacle detection in such conditions, leveraging their complementary strengths for robust perception. Real-time edge fusion is another underdeveloped area, as only 38.4% of systems perform full sensor fusion on embedded devices. Adapting optimized AI models, such as YOLOv5-tiny or MobileNetV3, for low-power on-board inference will enhance computational efficiency and enable real-time processing. Current detection ranges, typically limited to 10–20 meters, are insufficient for high-speed scenarios like highway driving. Research into radar-augmented LiDAR or novel sensor configurations is essential to achieve reliable detection beyond 50 meters, improving safety at higher velocities. Cost remains a barrier, with only 22% of systems using commercially affordable sensors. Shifting to solid-state LiDAR and low-cost radar, paired with streamlined software pipelines, will facilitate mass-market EV deployment. Context-aware risk prioritization is also underexplored, with fewer than 15% of studies implementing semantic obstacle classification to differentiate critical objects like pedestrians from barriers. Future algorithms should fuse spatial, semantic, and behavioral data to enable smarter risk assessments, enhancing decision-making dynamic calibration and health monitoring are notably absent, with less than 10% of systems incorporating self-calibrating or failure-detecting modules. Developing real-time calibration, sensor drift compensation, and redundant failover logic will improve system reliability. Finally, integration with V2X infrastructure is minimal, with under 5% of research exploring sensor-augmented V2X communication. Fusing LiDAR and radar data with vehicle-to-infrastructure updates via 5G networks can extend perception beyond line-of-sight, significantly enhancing safety and situational awareness. These research pathways aim to create scalable, robust, and intelligent obstacle detection systems for next-generation EVs.

13. CONCLUSION

This comprehensive review has explored AI-driven multi-sensor fusion techniques for real-time obstacle detection and environmental perception in AEVs, emphasizing how the integration of LiDAR, radar, vision, and thermal sensors with advanced deep learning frameworks enhances detection accuracy, robustness, and adaptability in varied conditions. Beyond summarizing existing methods, the study identifies critical challenges, including sensor calibration, adverse-weather resilience, real-time embedded processing, and cost limitations. The findings point toward the need for context-aware fusion frameworks that dynamically adapt sensor and algorithm selection based on environmental and operational conditions, coupled with V2X-enabled perception sharing to extend situational awareness beyond line-of-sight. For the research community, this work provides a consolidated knowledge base and a roadmap linking open problems with viable solutions, such as lightweight AI models for edge deployment, self-calibrating sensor arrays for improved reliability, and hybrid LiDAR–radar–thermal configurations for all-weather performance. For industry stakeholders, the insights highlight the potential for scalable, cost-effective fusion architectures to accelerate the adoption of level 4–5 AEVs in mainstream markets. Ultimately, the integration of robust sensor fusion with intelligent, adaptive decision-making will be central to delivering safe, efficient, and widely accessible autonomous transportation, and its success will depend on continued collaboration among academia, industry, and policymakers to ensure practical, regulatory-compliant implementations that benefit both road users and the broader smart mobility ecosystem.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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