# Blind Spot Detection Systems in Smart Vehicles: A Comprehensive Technical Review of Technologies, Methodologies, and Performance Analysis

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**Abstract**

*With the continuous rise in road traffic, blind spot-related accidents have become a persistent and serious threat to road safety, particularly involving large vehicles such as buses and trucks. Due to their size, these vehicles have significantly larger blind spots compared to passenger cars, leading to more severe and often fatal collisions, especially with vulnerable road users (VRUs) such as cyclists and pedestrians. As a result, there has been increasing focus on the development of Blind Spot Monitoring (BSM) systems, a critical component of Advanced Driver Assistance Systems (ADAS). These systems are designed to detect objects or vehicles in areas not directly visible to the driver, using technologies such as radar, ultrasonic sensors, and camera-based vision systems. Recent advances have incorporated deep learning algorithms and sensor fusion techniques to enhance detection accuracy and system responsiveness.*

*This review paper presents a comprehensive review of both traditional and modern blind spot detection methods, evaluating their effectiveness, limitations, and real-world applicability. In addition, this paper highlights a proposed vision-based approach using rear-view cameras, offering a low-cost yet reliable solution for blind spot detection in commercial vehicles. The study emphasizes the need for improved system integration, real-time performance and bidirectional alert mechanisms to prevent collisions and enhance overall road safety.*

## I. Introduction

The fatalities recorded annually counts to 1.9 million worldwide due to road traffic accidents and costs approximately 3% of the Gross Domestic Product (GDP) of each country [1]. While in most countries the main victims of road accidents are represented as vulnerable road users (VRUs) such as pedestrians, cyclists, and motorcyclists [1]; the Europeans mostly at risk are represented by vehicles' occupants (45%), followed by pedestrians (18%), motorcyclists (16%), and cyclists (10%) [2]. To guarantee both active and passive safety of road vehicles, it is essential to comprehend the primary elements that lead to road traffic accidents, along with the behavior of cars and occupants in these scenarios. Despite international and European objectives to halve global road fatalities by 2030 [3] and achieve zero fatalities in European countries by 2050, [4] the prevalence of road traffic accidents and associated mortality remains alarmingly high. In this regard, joint efforts from car and component manufacturers, policymakers, public authorities, and researchers are necessary to develop both passive and active safety systems that would eventually enable the implementation of high-level autonomous vehicles on a large scale.

Accidents involving VRUs are disproportionately likely to result in serious or fatal injuries and play an important role in accident reconstruction. One possible scenario in the inner-city environment is an accident between right-turning commercial vehicles and parallel pedestrian or bicycle traffic [5,6]. Due to the elevated driver's seat position and the non-full-surface glazing of the driver's cabs, areas near the commercial vehicle cannot be easily seen by the driver. These areas are called blind spots. To minimize this problem, the EU Directive 71/127/EEC [7] has prescribed several complementary mirror systems for commercial vehicles since 1971. As an additional problem, a heavy commercial vehicle's driver must pay attention to various potentially critical areas simultaneously, especially when turning in a limited space in an inner-city environment. It is often impossible to concentrate fully on a specific potential danger zone during the entire turning process. Cyclists move at a comparatively high speed and may only be perceptible for a short time in one of the exterior mirrors and can therefore be overlooked by the commercial vehicle's driver [8,9,10,11].

To compensate for this problem and thus noticeably reduce the number of traffic accidents, Regulation EU 2019/2144 of 27.11.2019 [12] successively introduced various driver assistance systems as mandatory equipment for newly type-approved or newly registered vehicles. In particular, to improve the perceptibility of VRUs for commercial vehicles with a maximum permissible mass of more than 3.5 t, a so-called blind spot assistant is required from 6 July 2022 onwards for newly type-approved vehicles and from 7 July 2024 for newly registered vehicles. Due to the increased risk potential because of their high speed, cyclists are explicitly targeted. However, the functionality of the blind spot assistance system also includes comparable road users, such as users of small electric vehicles and pedestrians. The technical characteristics of this assistance system and the required test methods are described in UN-ECE R151 of 25 September 2020 [13].

The main purpose of this paper is to review and focus on the type of blind spot detection technologies being implemented and evaluate the performance, accuracy, feasibility and practicality of such technologies.

Blind spots refer to areas around a vehicle that remain invisible to the driver using traditional mirrors. These blind zones are major contributors to accidents during lane changes, merges, and turns. According to the National Highway Traffic Safety Administration (NHTSA), an estimated 840,000 blind-spot-related crashes occur annually in the United States alone [1].

Blind Spot Detection Systems (BSDS) are safety mechanisms developed to address this hazard by continuously monitoring these zones and alerting the driver about nearby obstacles. BSDS can utilize various sensing technologies—ultrasonic sensors, radars, cameras, LiDAR, Bluetooth Low Energy (BLE), and deep learning algorithms—each with unique strengths and limitations. This paper offers a thorough technical review of each approach, detailing methodologies, system configurations, performance metrics, and practical feasibility.

## II. Ultrasonic Sensor-Based BSDS

### A. System Architecture

Ultrasonic sensors are widely used in cars for blind spot monitoring, which improves safety by identifying objects that the driver cannot see. The time it takes for high-frequency sound waves to return after colliding with obstructions is measured by these sensors. Wave frequency has an inverse effect on ultrasonic sensors' dissemination angle. Vehicles up to 40 kph can be detected by ultrasonic sensors. When ultrasonic waves go through the atmosphere, they attenuate due to absorption loss, diffraction and diffusion. The distance of an object from the sensor can be calculated as:

$d = t.vu/2$

where vu is the ultrasonic wave speed which depends on environmental factors such as temperature and their correlation can be formulated as:

$$Vu = 331.5m/s + 0.61T$$

Adnan et al. [14] proposed a BSDS using HC-SR04 ultrasonic sensors controlled via an Arduino Uno. Sensors were mounted near the vehicle's mirrors and monitored lateral space. The system used distance thresholds to determine proximity and triggered visual warnings. Ultrasonic sensors will detect approaching vehicles at low speed in any weather condition. The following are the most crucial elements in BSD:

- According to ISO17387, the system's response time should be less than 300 ms.
- The detection range, as required by ISO17387, must be at least three meters from the vehicle's sides.
- A vehicle's maximum detectable speed, as defined by ISO17387, should be at least 36 kph.
- Good performance under all driving circumstances.
- A comprehensive 360-degree view of the surroundings of the car.

**B. Performance**

- **Detection range**: ~1.5 m
- **Cost**: Very low
- **Real-time latency**: <100 ms
- **Limitations**: Inaccuracy in rain and wind; no object classification

Despite limitations, ultrasonic-based systems are effective for short-range low-speed scenarios and offer budget-friendly retrofitting solutions.

## III. Radar-Based BSDS

### A. FMCW Radar Principles

Radar, particularly Frequency-Modulated Continuous Wave (FMCW), is highly effective in medium to long-range detection. Kim et al. [15] introduced a BSDS using 24 GHz FMCW radar modules. The system used 2D Fast Fourier Transform (FFT) to extract Doppler and range information, followed by Kalman filtering for object tracking and MUSIC for angle-of-arrival (AoA) estimation. However, this technology is for pedestrian detection and not for automotive applications. The utilization of both 2D FFT and multidimensional FFT techniques have been discussed in this paper. The FMCW-powered BSD radar system continuously emits signals while driving, which bounce off nearby objects and return to the vehicle. This technology may calculate the distance, angle, direction, and speed of the target vehicle; evaluate the driving circumstances; calculate the probability of a collision with the vehicle; and notify the driver in order to ensure the safety of driving a car. Tracking algorithms for determining the vehicle's surrounding situation, procedures for tracking target vehicles in the surrounding environment and signal processing technology—which determines the surrounding situation by analyzing the reflected signals after transmitting a signal—are the primary technologies utilized in the design of the BSD radar system. The clutters in this study exhibit Rayleigh distribution and were taken from the real application environment. The digital filter bank, which efficiently suppresses noise by lowering the side lobe strength, was used to filter the intermediate frequency signals first.

In metropolitan settings, the system's early alarm rate reached 98.20% and 98.21% throughout the day and night, respectively. The suggested approach has a greater alert rate than previous visual blind spot identification and warning systems. The findings demonstrate that the suggested approach may successfully warn drivers in advance and avert collisions.

### B. Enhanced Detection with CFAR

The constant false alarm rate target detection method, or CFAR, is frequently employed in radar systems. The radar target recognition method uses a power detection threshold to identify targets that are impacted by clutter reflections from the land, water, etc. The fixed detection power threshold is unknown as the clutter power is uncertain. Adaptively resetting the detection threshold is necessary to fix this issue. The neighborhood resolution cells' average amplitude is used to determine the clutter background noise power level under test. The estimated background noise level value is scaled according to the intended false alarm likelihood to get the power detection threshold. The CA-CFAR detector, which stands for cell-averaging constant false-alarm rate, was proposed by Finn and Johnson. Liu et al. [16] enhanced target detection algorithm; a cell greatest, smallest and averaging constant false-alarm rate target detection algorithm; known as CGSA-CFAR, which is based on the Rayleigh clutter distribution model maintains a higher detection rate and a lower false-alarm rate by adjusting the power detection threshold in time based on the noise power level, which was estimated using the proposed target detection algorithm. This method improved object detection accuracy even in noisy environments.

### C. Evaluation

- **Detection accuracy**: >98%
- **Latency**: <100 ms
- **Environmental resilience**: Excellent in fog, rain, and night
- **Use case**: Suitable for autonomous and semi-autonomous vehicles

## IV. Vision-Based BSDS

### A. Image Processing Techniques

Wu et al. [17] developed a BSDS using a rear-view camera, employing shadow and edge detection (HESCR) during the day and bright object segmentation for nighttime detection. An efficient blind spot warning system (BSWS) for both daytime and nighttime settings is developed by Wu et al. [17]. The dynamic calibration camera models are daytime and nighttime blind spot detection (BSD) algorithms which are part of the proposed BSWS. The Horizontal Edge and Shadow Composite Region (HESCR) technique is used in the suggested system to extract the searching region and determine the shadow position of the targeted cars throughout the day. Furthermore, the suggested method detects the paired headlights of the targeted cars for the BSD and extracts bright objects to identify automobiles during nighttime road sceneries. An embedded platform based on DSP is used to implement the BSWS. The suggested BSWS is practical for vehicle recognition and collision warning in a variety of daylight and nighttime traffic conditions, according to experimental findings.

In this study, Jung and Yi [18] suggested a vision-based monitoring system that uses a rear-view camera to identify cars in a blind-spot region. They employed well-defined detection windows with fixed location and size, histogram of oriented gradients (HOG) and the support vector machine (SVM) to detect a vehicle in each detection window rather than navigating the entire image in search of a vehicle. They calculated the velocity vector of the detected car to see if it was getting close to the target vehicle or not. Ultimately, the warning signal is produced using the past occurrences. They used a rear-view camera to record several types of sequences in order to assess the BSM algorithm's effectiveness. According to experimental data accuracy is greater than 98%.

Kwon et al. [19] employed Long Short Term Memory (LSTM) networks to identify the key regions of the photos and Convolutional Neural Networks (CNNs) to identify items in the image. Fully Connected Networks (FCNs) has been used to dynamic picture data for real-time dynamic images. The capacity to identify an automobile utilizing any portion of the vehicle (any characteristics in a front or side view) in a designated region of the dynamic pictures is necessary for the FCNs-based blind spot detection task. In order to determine whether the detected automobile is in an adjacent lane or far away, the framework must also detect the diagonal distance of the car in that lane. The primary techniques for this are: 1) feature extraction from the Histogram of Oriented Gradients (HOG), 2) Sliding window, 3) A heatmap. In order to train FCNs to identify the automobile during the learning phase, this proposed framework first extracts HOG features of the pictures for the red, green and blue color dimensions of the training images. Sliding windows are used in the initial stage to sample only particular areas of the pictures and to capture several samples by adjusting the window's height and size. FCNs are then supplied each sample with red, green and blue dimensions in order to make predictions. In order to prevent false positives, the heatmap is used to pinpoint the positive prediction area. The less hot regions are then filtered away. The car's detection region is the boundary of many heat concentrations in the heatmap. To lessen false positives, the framework once more eliminates rectangles smaller than a threshold from certain regions, such as automobile shadows or vehicles not in the immediate next lane. Cars in the blind spot are detected using the remaining rectangles. The FCNs use AdamOptimizer and Relu activations, and the following hyperparameters must be learned in this network: 1) Rate of learning 2) The quantity of layers that are hidden 3) The quantity of concealed units 4) Heatmap concentration 5) The size of a rectangle.

**B. Performance**

- **Accuracy**: ~95% under ideal conditions
- **Limitations**: Reduced performance in low light or when lenses are obstructed
- **Advantages**: Affordable, capable of object classification

**V. BLE and IoT-Based BSDS**

BLE systems are designed to protect vulnerable road users (VRUs) such as cyclists and pedestrians. De Raeve et al. [20] proposed a blind spot identification and warning system that uses Bluetooth Low Energy (BLE) wireless communication and Received Signal Strength Indicator (RSSI) measurements. After threshold filtering the incoming RSSI data, a sliding window filter is used to impute a weighted average. Rain, snow, garbage cans, etc. are typically also recognized, which results in a large number of undesired false positives. This study proposes a BLE-based detection and warning system that alerts the vulnerable road user and the truck driver to a possible threat. Furthermore, the main issues with camera and radar-based detection systems are resolved because the system is based on radio frequency transmission.

A comprehensive detecting area is created around the truck using the approach suggested in this study. As a result, a detection node is placed at the truck's front and back and three nodes are evenly spaced along the right side. The road user who is at risk has a wearable or tiny sensor that is wirelessly linked to every detection node. As a result, when a road user enters the blind spot, the susceptible individual can be identified. Bluetooth Low Energy (BLE) serves as the foundation for communication between the nodes in the suggested system. Because of its low power consumption, low complexity, affordability, ease of integration with smartphone apps and compatibility with next versions, this communication standard was chosen.

**Key Outcomes:**

- **Detection range**: 3–8 m
- **Latency**: ~50–100 ms
- **Advantages**: Low-cost, energy-efficient
- **Limitations**: Beacon must be worn by VRUs

**VI. LiDAR-Based Systems**

Naik et al. [21] proposed LiEBiD, a LiDAR-based early blind spot detection system using the SICK LMS111 LiDAR sensor which provides early warnings with regard to the proximity of other vehicles in “no zones” and “blind spots”. An essential component of the Advanced Driver Assistance System (ADAS), this product offers prompt remedial action to avert an impending collision. Additionally, it produces far more accurate findings with the aid of Triangulation Range System Resolution. Since the LiEBiD system categorizes barriers for three distinct threshold limit zones for early detection and warning, it is very successful in real-time proximity sensing. Three distinct thresholds that represent the safe zone for lane changes, the zone for cautious lane changes and the point at which it is recommended that drivers refrain from changing lanes have been programmed into the LIDAR. The LIDAR continually alerts the driver when it identifies obstructions that may be moving or stationary. The LiEBiD product has an advantage over its competitors since the suggested system has a reaction time of less than 500 µs, which is ten times quicker than the current methods, which have response times of milliseconds.

- **Angular resolution**: ±0.25°
- **Response time**: <500 µs
- **Use case**: High-end autonomous vehicles
- **Drawback**: High cost and integration complexity

**VII. Deep Learning and Fusion-Based BSDS**

**A. YOLOv4-Based Detection**

Chang et al. [22] used stereo cameras with YOLOv4 on a Raspberry Pi 3B+ to detect motorcyclists near buses. The system could identify rearview mirrors and compute distance in real time, improving safety in urban traffic scenarios. Chang et al. [22] developed a proactive bus blind spot warning (PBSW) system that would alert motorcycle riders as soon as they approach a target vehicle, such as a bus, that is in the blind spot or the region of the inner wheel difference. This will improve BSD's real-time capabilities and perhaps significantly improve motorcycle safety. The suggested hardware, which includes a dual-lens stereo camera and a Raspberry Pi 3B+, is mounted on the motorbike. They created stereoscopic pictures using dual-lens cameras, then sent them from the Raspberry Pi 3B+ to a cloud server over a cellular network and an Android phone via Wi-Fi. The location of the bus's rearview mirror was determined using the YOLOv4 image recognition model on the cloud server and the distance between the bus and the motorcycle was estimated using the lens imaging concept. Lastly, the PBSW app on the Android phone receives the estimated distance from the cloud server. The app will show the viewable area/blind spot, the area of the bus's inner wheel difference, the motorcyclist's position and the projected distance between the motorbike and the bus based on the distance value that was received. Therefore, to improve the rider's real-time safety, the app will instantly notify them if they approach the bus' blind spot or the inner wheel difference region.

This PBSW technology has been tested in practical settings. The findings indicate that the average round trip time between the Android phone and the cloud server is around 0.5 seconds, the average position accuracy of the rearview mirror is 92.82% and the error rate of the calculated distance between the dual-lens camera and the rearview mirror is less than 0.2%. One of the best systems that may be used in the real world to protect motorcycle riders from the risk of going into the target vehicle's blind spot and inner wheel difference region in real time can be PBSW system.

- **Accuracy**: 92.82%
- **Communication delay**: ~0.5 seconds

**B. RNN and FCN Models**

Shen and Yan [23] implemented an RNN-based system to predict object movement in the blind spot using temporal video data.

Shen and Yan [23] have presented a technique that uses footage from the car's mounted cameras to identify and notify a driver when a car enters their blind areas. Their study examined two methods for identifying blind spot situations. The highest likelihood that this condition will occur was then determined using hidden Markov model (HMM). The result, however, fell between 0.31 to 0.40, which is insufficiently high for an effective parameter. Thus, it was found that HMM probably doesn't make sense in this experiment. In next method; following data collection; RMSEs were computed, future sequences were predicted and results were analyzed using RNN. Lastly, the RNN analysis findings demonstrate that the RMSE is extremely low, ranging between 0.013 and 0.35, indicating a comparatively high level of accuracy for this blind spot monitoring system.

Kwon et al. [19] deployed FCNs trained on vehicle datasets for classification and tracking. Dynamic picture data has been utilized for real-time dynamic pictures using Fully Connected Networks (FCNs). For the FCNs-based blind spot detection job, the ability to recognize a car using any part of the vehicle (any features in a front or side view) in a specific area of the dynamic images is required.

**C. Multi-Sensor Fusion**

Shirahmad et al. [24] presented a hybrid BSDS integrating radar, camera, LiDAR, and ultrasonic data to leverage the strengths of each sensor. The system significantly improved detection robustness and minimized false positives. By analyzing the limitations and characteristics of each sensor, the author here suggests a sensor topology for the BSD system. When building a BSD system, a number of elements need to be taken into account, including sensors' field of vision (FOV), different driving circumstances, system's total reaction time and environmental influences. It should be mentioned that in order to improve the detection ratio and accuracy, the whole blind area must be covered by the overlapping FOV of the sensors. Additionally, the BSD system needs to work properly in all driving situations, such as turning a corner or leaving a parking lot. According to ISO17387, the whole system reaction time should be less than 300 ms. If it above this threshold, the likelihood of an accident would increase.

One of the most crucial elements is the processing time of the sensors, which is around 100 ms Lidar sensors at high precision settings. We may infer that the requirements for vehicle identification under different situations cannot be fully satisfied by single-sensor-type BSD systems. Consequently, using at least two distinct kinds of sensors is required, which implies that BSD should use sensor data fusion techniques. To improve performance and lower uncertainties, data fusion can compensate for sensor flaws. Shirahmad et al. concentrated on sensor data fusion for sensor topology in the BSD system because of the fusion technique employed in R Omar et al. [25] and its encouraging outcomes. Improved accuracy and lower false alarm rates have resulted from fusion at the detection level. Radars can give information about the vehicle's range and radial velocity in the sensor configuration. Lidar sensors can give an object's shape and provide cameras a region of interest (ROI). Lidar sensors supply the ROI, which cameras may use to identify and categorize things. To accomplish the intended goal of the BSD system, the data gathered from these three sensors may be combined.

## VIII. Comparative Analysis

| System Type | Accuracy | Cost | Range | Latency | Robustness | Ideal Use Case |
|---|---|---|---|---|---|---|
| Ultrasonic [14] | Moderate | Very Low | Short | <100 ms | Low | Low-speed and retrofitted vehicles |
| Radar [15][16] | Very High | High | Long | <100 ms | Very High | Premium cars and all-weather driving |
| Vision [17-19] | High | Medium | Medium | <50 ms | Medium | Urban settings, good lighting |
| BLE [20] | Moderate | Very Low | Short | <100 ms | High | VRU protection in cities |
| LiDAR [21] | Very High | Very High | Long | <1 ms | High | AVs and delivery fleets |
| Deep Learning [22–24] | Very High | Medium-High | Medium | <300 ms | Medium | Predictive, intelligent systems |

## IX. Conclusion

Blind Spot Detection Systems have evolved from basic proximity detectors to complex, intelligent safety solutions. Radar and vision-based systems currently dominate commercial use, while BLE and LiDAR technologies are emerging for specific applications. Deep learning and sensor fusion offer enhanced prediction and contextual awareness.

**Future Directions:**

- **Edge computing** for real-time inference
- **Standardization of datasets** for model training
- **Multi-sensor fusion** to enhance accuracy and reliability
- **Integration with V2X** for cooperative safety mechanisms

BSDS technologies will continue to play a vital role in transitioning toward fully autonomous and safe transportation systems.

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