

Road Traffic Safety Measures: Lab Testing on Collision Avoidance

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Abstract

The increasing traffic volume necessitates robust collision avoidance. Modern vehicles employ advanced sensors like radar, LiDAR, and cameras for real-time data processing (5G collision avoidance). However, not all road users are equipped with such technology, especially vulnerable ones like pedestrians. The proposed approach for setting up a collision avoidance system involves utilizing a camera including internal object recognition capabilities. Additionally, the camera features functions allowing the definition and observation of specific regions as vehicles traverse them. In a laboratory setup, model vehicles follow predefined paths, and collision-prone regions along these paths are identified. The camera's extended functions, accessible via its dashboard, capture and analyze the behavior of moving objects within these regions. This approach enables a comprehensive examination of potential collision scenarios and facilitates the development and testing of collision avoidance algorithms.

This paper provides an overview of utilizing the Bernard Mobility Analyzer (BMA) which is an intelligent optical system for identifying objects for monitoring, control, and guidance. It consists of a camera system that, supported by an internal controlling unit and artificial intelligence, recognizes objects, and only processes and transmits this anonymous information. The camera is deployed for functions such as trajectory prediction and collision avoidance. The paper covers the experimentation methodology, including challenges, along with settings for obtaining relevant data. Insights are given into the communication protocol, platforms used, and overall architecture. In conclusion, a simplified collision warning system could be set up on a laboratory scale.

Keywords: 5G, Collision Avoidance, Road Traffic, Lab Experimentation, Computer Vision

Introduction

Collision avoidance is an indispensable function across various domains, encompassing manufacturing, transportation, robotics, and aviation. These systems are pivotal in ensuring safety, enhancing efficiency, and minimizing costs. For example, in modern automobiles, collision avoidance systems utilize sensors and algorithms to detect obstacles on the road, such as pedestrians or other vehicles [1]. When a potential collision is detected, these systems can automatically apply brakes or provide warnings to the driver, helping to prevent accidents and ensure the safety of everyone on the road. The increasing road traffic emphasizes the importance of implementing robust collision avoidance systems to prevent accidents [2]. The goal of reducing traffic has also been pursued intensively in research for several years. Contemporary vehicles are equipped with

various sophisticated sensors and onboard electronics featuring rapid real-time processing capabilities.

The approach described in the following paper is based on the architecture [3]. In a downscaled indoor lab setup, the images captured by the Bernard Mobility Analyzer (BMA) [4] are utilized for data analysis, aiding in assessing vehicle positioning and identifying potential collision scenarios. Through various scenarios, the system can pinpoint collision-prone situations. Subsequently, warning signals are generated to mitigate collisions, enhancing overall safety measures. To implement collision avoidance using data from the BMA additional methodologies and technologies are used alongside to navigate objects along their intended paths. Integrated with inputs from the camera, machine learning algorithms predict patterns, allowing vehicles

to make decisions. The designed path-planning algorithms generate feasible trajectories using camera data, to issue warnings at risk intersections to prevent collisions. Leveraging low-cost sensors and partially autonomous capabilities, various scenarios can be emulated to evaluate the effectiveness of collision avoidance systems. The paper will further elaborate on the implementation approach and experimental methodology in subsequent sections.

This paper is organized accordingly: Related work and previous research are outlined in the next section. Then, the approach and setup are shown, followed by a section describing the methodology. The observations and results are presented in the sections afterwards and finally, a conclusion and an outlook are given.

Related Work

Research in collision avoidance and road safety spans various domains, with recent studies focusing on innovative approaches to mitigate risks and enhance safety for all road users. The paper "CAR-2-X and Pedestrian Safety" [5] introduces concepts for road users to exchange position data and warnings via cellular networks. The study "Impact of Roadway Characteristics on Intersection Crash Severity" [6] examines factors such as pavement friction and lighting, emphasizing the importance of considering roadway characteristics in crash severity analysis. A study on Real-Time IoT-Architecture for Collision Avoidance in Smart Cities based on the 5G Mobile Technology is proposed in [3]. Another contribution is the research on "Vulnerable Road Users' Safety in Infrastructure-Assisted ITS" [7] which proposes a VRU awareness message exchange mechanism to increase reaction time and prevent collisions using innovative communication strategies. The development of a "Vehicle-Mounted Detection and Collision Avoidance System" [1] addresses factors like vehicle speed and safety distance to enhance road safety through comprehensive collision avoidance measures. Other studies, such as "Traffic Collision Detection Using DenseNet" [8] and "Enhanced V2X Pedestrian Collision Avoidance System" [9] explore advanced technologies like deep learning and V2X communication to detect and mitigate collisions, emphasizing the integration of diverse sensor sources for informed vehicle responses. Research efforts include initiatives like "Smart City IoT Application for Road Infrastructure Safety and Monitoring" [10] which leverages the Digital Twin concept to

enhance road safety and infrastructure management through real-time data processing. These diverse contributions highlight the evolving landscape of collision avoidance research and the importance of integrating advanced technologies and communication strategies to enhance road safety and mitigate risks effectively.

Approach and Setup

The laboratory setup described is aimed at providing a controlled, dynamic environment for the exploration of intersection scenarios. Predefined paths serve as the basis for vehicular experiments, incorporating key features to emulate real-world conditions. Figure 1 shows the experimental setup that comprises a combination of remote-controlled cars and autonomous vehicles programmed for path following. This setup enables the investigation of both human-controlled and automated behaviors in the same controlled environment. The path design includes intersection zones, where vehicles may cross paths. These intersections are modeled to replicate common scenarios encountered in real environments. To facilitate the study of trajectory dynamics [11], extended sections of the route are configured to allow multiple vehicles to travel simultaneously along the same path. This design choice facilitates the observation of how vehicles interact when navigating shared paths, an essential consideration for the integration of autonomous vehicles into mixed traffic scenarios.

The requirements for the model vehicles include cost-effectiveness, realistic functionality (such as real steering), appearance authenticity (for recognition by camera-based sensors), collision robustness, and safe operation in proximity to people without additional protective measures like fencing or boundaries. Considering these requirements, scaled RC (Radio Controlled) model vehicles were chosen. These vehicles offer affordability, accessibility, and safety, making them suitable for experimentation without significant financial investment. In [12] challenges of basic functions for autonomous vehicles are experimentally evaluated using similar low-cost sensors and model vehicles. The chosen models provide space to integrate additional components like sensors and cameras while remaining small enough to reduce the risk of accidents during testing. Their versatility allows for customization according to specific project requirements, making them feasible for collision detection experiments.

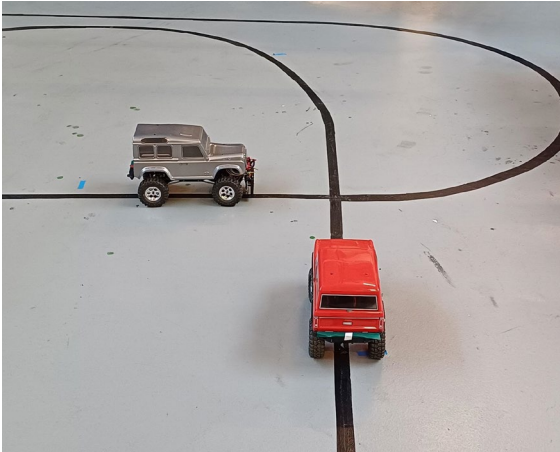


Fig. 1: Intersection scenario – lab setup.

To ensure scalability and accurate representation, the objects used in experimentation are scaled down to a ratio of 1:10 concerning real-world dimensions. This scaling factor maintains fidelity while optimizing space utilization within the laboratory setup. The positioning of observation equipment, particularly the camera, is paramount for precise data collection. Utilizing lens calculators [13] and empirical testing, the optimal height for BMA Camera lens placement is determined to be 1.45 m from the ground, ensuring coverage of the designated tracks. The horizontal position on the floor was determined empirically. From a lateral view, the camera is placed at 2.8 m ground distance in front of the tangential path, as shown in Figure 2. The ground distance to the center of the intersections is 3.1 m, each. The camera's horizontal angle of view of 103° allows it to capture approximately 7 m at the first tangential path, allowing the entire oval in front of the camera to be observed.

The BMA Camera is equipped with the added feature of a dashboard that allows the definition of various functions based on object identification and trajectory mapping. The main functions implemented through the BMA that pertain to the application of collision avoidance are introduced in this section. Traffic and Parking model: This model detects vehicles, riders, and persons in dynamic scenes (e.g., urban traffic or highways where objects move fast). This model comprises of the following functions:

"ROI" – Region of Interest: This function is used to count objects in this region. Trigger options can be chosen that are then used to be saved at regular intervals (e.g. 10 s) or when the state of the zone changes (e.g. parking lot surveillance – a car leaves the parking zone).

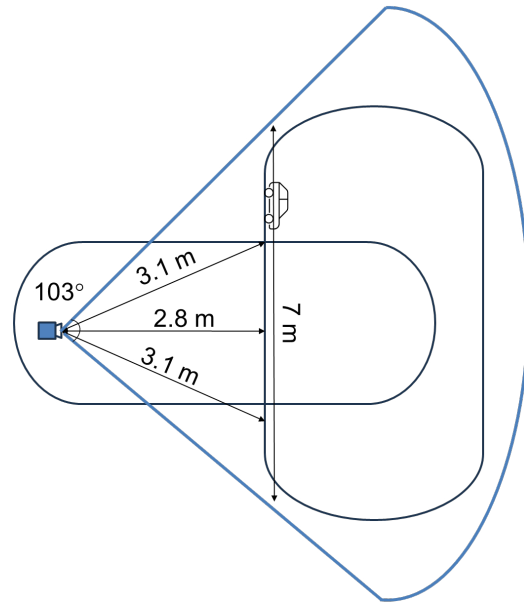


Fig. 2: Sketch of lens coverage.

A region of interest event is triggered either by a status change or by a time interval triggered (property trigger type). The property state can change from occupied to free and vice versa. Each event has a custom name (property roiname) and a timestamp (property timestamp) when the event occurs. Detected objects and the associated class are listed (property objects). The classes depend on the use case and can be "car", "truck", "person", etc.

"CL" – Counting Line: Every time the center of the object passes through the line, it is counted. Counting lines can trigger traffic events, and speed measurement can be enabled by setting up a second counting line with a user-specified distance between them. A crossing line event is triggered as soon as an object crosses a virtual line (marked through the property lineId). The line has a custom name (property lineName). The object can have lines crossed in two directions (property direction) and move either in or out. In addition, the object that crosses the line is classified (property class).

"OD" – Origin/Destination: In this approach, regions of interest for observation are defined, encompassing both entry and exit points for objects. This method is particularly effective for dynamic data, as it triggers output when objects move between defined zones. By implementing overlapping regions, collision areas can be identified, to monitor and gather entry-exit data for analysis of collision risk and collision avoidance.

In the architecture depicted in Figure 3, there are four main modules: data collection, data analysis, warning generation, and output of warning messages or signals. This setup involves collecting and analyzing data to detect potential collisions. When a risk is identified, the warning module generates a message sent to the output module, which communicates the warning to relevant parties such as drivers, nearby vehicles, or vulnerable road users. The BMA Camera serves as the sensor component. The architecture illustrates the flow of retrieving MQTT [14,15] data from the BMA, using common technologies. Converting the data into JSON format using Node-RED [16], which is then stored in MongoDB [17] for analysis and collision detection algorithm development. This data includes information on region occupancy, vehicle trajectories, and entry-exit patterns of road users, all of which are time-stamped for analysis.

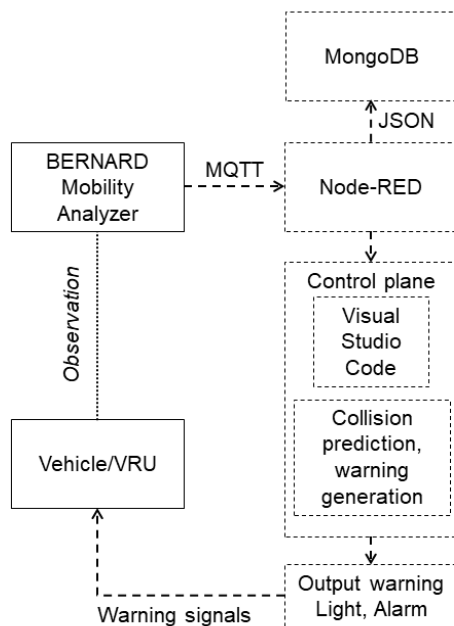


Fig. 3: Overall architecture.

Methodology

The experimental framework is conducted within a laboratory environment, to emulate real-world driving scenarios. The primary methodology employed for collision detection and avoidance revolves around trajectory mapping. By mapping the paths of automated vehicles within the laboratory environment, potential collision points are identified and analyzed. An algorithmic approach is adopted to issue collision warnings. Integral to the experimental framework is the utilization of the BMA Camera dashboard functions.

The experiment methodology employs three functions: ROI identifies collision zones, CL tracks object paths, and OD monitors the movement of origins and destinations, crucial for capturing data on object interactions. To evaluate system responsiveness, the experimental setup analyzes timestamps from each output to measure time intervals between transmissions. This enables the detection of any delays between component transmissions and notifications. An essential aspect of the experimental setup involves evaluating system performance under diminished illumination. Enclosing the designated area within structures to limit external light and subjecting the collision avoidance system to scenarios of reduced visibility, the study aims to assess its robustness and reliability in challenging lighting environments.

These parameters derived from the observations encompass object presence/identification, object movement between zones, object presence within specific ROIs and object movement across defined lines. The data includes object IDs, observed functions (ROI, CL, OD), function outputs, and corresponding timestamps for each observation or output received. Additionally, coordinates of bounding boxes surrounding objects in the analyzed images are obtained to track object movement between positions.

The objective of the methodology is to record output data generated when objects, whether static or dynamic, alter their positions at different speeds or traverse various regions. Through the ROI function, data indicating object presence within specific boxes is collected. Changes in output are noted as objects transition between regions to map their paths. Observation focuses on identifying when objects reach intersection regions, particularly examining instances where multiple objects approach the same intersection area simultaneously or sequentially.

Data obtained from the OD function delineates zones through which objects or modeled vehicles traverse. This information, combined with basic object ID, timestamp, and bounding box coordinates, provides understanding of object paths and entry/exit zones. Recognition of object direction aids in discerning whether objects, including multiple ones, are moving toward the same zone concurrently or successively, facilitating analysis of object movement and presence within intersection zones.

The CL function, in addition to basic information such as timestamps, object IDs, and bounding box coordinates, registers when objects cross counting lines. By placing consecutive counting lines in the region, the movement of objects along defined trajectories is mapped. Speed estimation between two counting lines further enhances analysis, offering insight into object behavior around the intersection zone.

The provided image illustrates the designated zones and areas subject to observation within the camera's scope. In Figure 4, the implementation of the ROI is depicted, where regions R1 and R3 are identified as collision-prone zones. Objects traversing along the horizontal and vertical tracks within these zones are susceptible to collisions, contrasting with the lower collision risk associated with region R2.

Figure 5 portrays the implementation of the CL function. As the object progresses along lines CL1 to CL4 on the predefined path, observations are made when it crosses each counting line. Entry into CL1 signifies presence within a collision-prone zone, signalling the potential for collision should another object traverse the same path toward that zone.

Figure 6 illustrates the implementation of the origin/destination OD zone function, enabling analysis of object movement direction. Observations are made based on the zone from which the object departs and the zone into which it moves. Red-colored boxes denote collision-prone zones, where objects are carefully monitored when present within these areas.

Results

This section analyzes observations from experimental functions with each function (CL, ROI, and OD) tested for five iterations in the collision detection framework to evaluate their performance under different conditions. Within each experiment, the moving car/object traversed the path a minimum of ten times to ensure precision and consistency in output patterns. Among the five rounds of experiments, certain functions were tested with multiple moving objects to simulate collisions. This testing methodology aimed to analyze output data and develop strategies to prevent collisions.

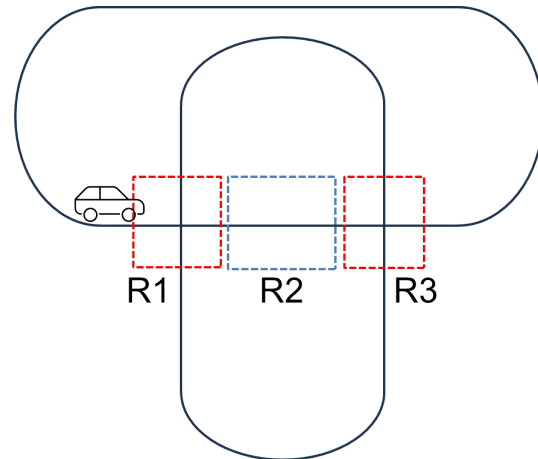


Fig. 4: Region of Interest function.

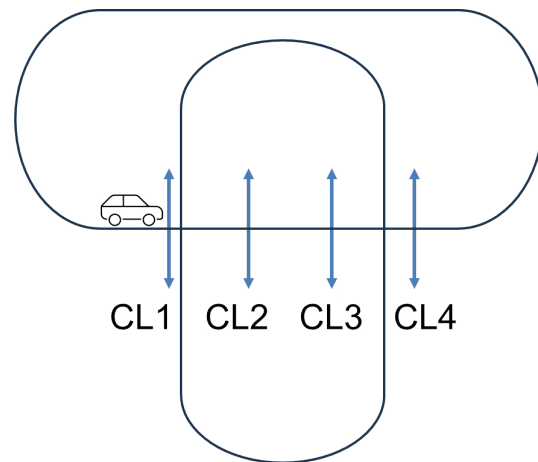


Fig. 5: Counting Lines function.

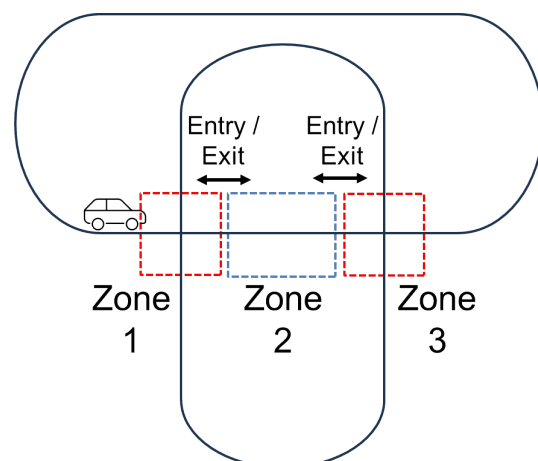


Fig. 6: Origin/Destination Zone function.

Accuracy and sensitivity for the ROI, CL, and OD functions were computed using the confusion matrix derived from experimental data. True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) were tallied to determine accuracy and sensitivity. Accuracy represents the proportion of correct classifications (TP and TN) out of the total instances, while sensitivity measures the proportion of correctly identified positives (TP) relative to all actual positives (TP and FN). These metrics offer insights into the functions' performance in object detection, movement tracking, and collision prediction. The percentages represent the relative performance of object detection instances within specific categories like ROI, CL, and OD, for the same object ID in that category. Accuracy and sensitivity metrics are derived from the confusion matrix, indicating the model's performance in identifying TP, TN, FP, and FN values across these categories. Minor deviations may arise due to slight variations in total instance counts used for calculations.

Figure 7 presents an analysis of the results obtained from experiments. According to the methodology, data from the BMA is stored in the database and analyzed for the measure of success ratio under different scenarios. The measurements are compared against the true scenario (according to the conditions of the experiment).

The ROI function reveals its capability to detect objects within predefined regions with an accuracy of 71%. This result includes 78% of true positive outputs. The function's ability to provide spatial information for collision prediction is highlighted. The findings emphasize the importance of an object's proximity to the ROI box midpoint for accurate detection. With a sensitivity of 63%, the ROI function shows potential in identifying objects

within collision-prone zones, enabling timely warning signals to prevent collisions as objects traverse through these areas.

In evaluating the OD function, its efficiency in capturing object movement between designated regions is highlighted. With a sensitivity of 56% and an accuracy of 67%, the OD function demonstrates its suitability for dynamic scenarios, as entry/exit data absence in static environments represents its dynamic nature. Scenario-based analysis is implemented for identifying potential collisions at regional intersections. The synchronization of object entry and exit is important in determining collision probability to mitigate collisions.

The CL function serves for trajectory mapping and speed estimation, with an accuracy of 76 % and a sensitivity of 69 %. Object presence is confirmed after the midpoint of the object passes through the line, with directional indications of its movement toward or away from the observable region. Speed estimation, typically ranging from 0.3 to 0.6 m/s, aids in further analysis of collision probability based on object speed towards the collision warning region. Leveraging this data, an algorithm is formulated to detect instances where objects traverse the observed collision region at higher speeds, triggering collision warnings to enforce avoidance measures. When scaled up to real-world objects, the speed range of 0.3 m/s to 0.6 m/s corresponds to approximately 10.8 km/h to 21.6 km/h. This speed range can be considered as the speed at which the original objects would move if tested in a parking garage scenario.

An algorithm written in Python is developed to provide trajectory information based on object movement across counting lines. The algorithm facilitates the identification of probable collisions based on trajectory matching, demonstrating the system's capability to track multiple objects and predict collision scenarios accurately. A warning signal is generated when the object enters the observed probable collision area where other objects are detected in that area bypassing that counting line. The collision warning signals are provided by analyzing the data from the ROI function and OD that indicate the presence of the objects in the region at the time and in which direction they move out of/in respectively.

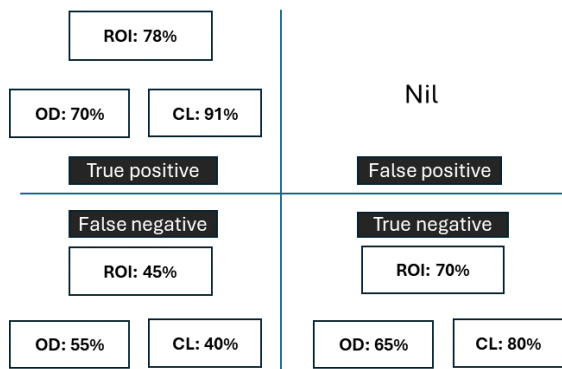


Fig. 7: Confusion matrix of results.

Figure 8 presents an analysis of time intervals, reflecting the duration from BMA output to screen presentation via Node-RED. The first graph displays all observed intervals, offering a comprehensive view of the processing landscape. The second graph focuses on intervals less than or equal to 50 ms, showcasing instances without outliers. These intervals capture Node-RED's processing time. The intervals are computed by comparing consecutive output timestamps from the BMA. In the context of Node-RED operations, these time intervals serve as a proxy for Node-RED's processing efficiency, excluding transmission intervals. Short intervals signify swift processing, while longer intervals may indicate processing bottlenecks or delays in data handling. For the overall time intervals, the analysis shows a maximum of 1996 ms. The mean interval duration stands at approximately 36.9 ms. The standard deviation for these intervals is 213.7 ms. Statistics for time intervals without outliers (i.e., less than or equal to 50 ms) reveal a maximum of 15 ms. The mean interval duration is approximately 1.3 ms. The standard deviation for these intervals is about 2.4 ms. These findings can guide further optimization efforts and considerations when deploying the system in a collision avoidance application. In particular, the outliers should be eliminated.

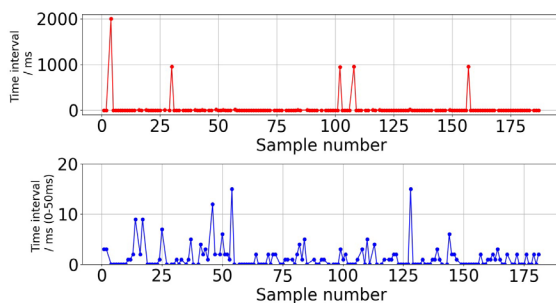


Fig. 8: Time interval plot.

The dim light experiments yielded results indicating effectiveness among the ROI, CL and OD zone functions. While the object identification function can be reliable under reduced visibility, other system functionalities exhibited limitations. The data collected for the object identification function in dim light conditions revealed an accuracy of about 77%. This accuracy percentage was calculated by filtering all outputs from the experiments that correctly identified objects as cars, dividing them by the total iterations, and calculating the percentage. When object identification was performed under normal light conditions, it demonstrated an accuracy of 94%, which is corresponding to the documentation [18].

Conclusion and Outlook

Based on the experimental setup and the various scenarios explored, the BMA camera demonstrates utility in analyzing images that closely replicate real-world scenarios. While it excels in observing predefined zones to monitor vehicle/object movement, it falls short in scenarios requiring video monitoring due to imprecise output and intermittent detection. Enhancements are warranted to render the device more adaptable, precise, and consistent across diverse scenarios. This entails equipping it with features conducive to precise detection and adaptable functionality under varying conditions. Integrating external sensors can serve to enhance overall system reliability. Following laboratory experimentation, the chosen approach proves beneficial for exploring collision scenarios and devising mitigation strategies. The utilization of RC model vehicles facilitates iterative experimentation at minimal cost, mitigating energy expenditure and ensuring safety within the controlled laboratory environment. The indoor setting eliminates external factors like weather and traffic, streamlining experimentation processes. Inherent limitations impede the comprehensive exploration of all desired scenarios. Scaling down objects and environments can limit the effective utilization of BMA functions, impacting the successful implementation of collision detection systems. However, the object identification worked as reliably as specified in the documentation.

In future, the system should feature adaptable sensors capable of real-time adjustments and interactive platforms for dynamic input modification and output analysis. Incorporating video analysis capabilities and object tracking IDs can enrich scenario evaluation and facilitate precise observation amidst varying traffic densities. By addressing these considerations, the efficacy and versatility of collision avoidance systems can be markedly improved in laboratory settings. Exploring delay measurements and performance in low-light conditions presents promising avenues for further study. Refining methodologies for assessing system responsiveness and enhancing accuracy using advanced microcontroller technology and precise sensors could enhance the system's performance. Investigating the impact of various scenarios and environmental conditions on delay measurements can optimize collision detection systems. Addressing challenges posed by reduced visibility requires innovative solutions, such as augmenting sensor capabilities with advanced imaging technologies and

developing algorithms tailored to low-light conditions. Simulating and testing scenarios under different lighting conditions can refine strategies for optimizing system performance and enhancing road safety.

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