

A VLC-Enabled Collision Avoidance System Using Visible Light Positioning and Edge Detection

Rakesh Ranjan¹ and Seema Dwivedi²

¹Department of Computer Science and Engineering, ABES Engineering College, Ghaziabad, U.P. INDIA

²Department of Computer Application, Axis Institute of Higher Education, Kanpur, U.P. INDIA

Email: iiirakeshranjan@gmail.com

Research Paper

Received: 11 Jan 2026, Revised: 16 March. 2026, Accepted: 7 Apr, 2026

Abstract:

The rapid evolution of autonomous and intelligent transportation technologies has increased the need for dependable real-time collision prevention systems. This study introduces a vehicle-to-vehicle communication framework based on Visible Light Communication (VLC), integrating Visible Light Positioning (VLP), centroid extraction techniques, and Angle-of-Arrival (AoA) localization for accurate vehicle tracking and collision risk assessment. In the proposed approach, LED-based automotive lighting components, including headlights and taillights, serve a dual purpose by providing illumination and transmitting positioning information simultaneously. A camera-equipped receiving unit captures optical signals and applies image-processing algorithms to identify object centroids and estimate their locations. The spatial coordinates of surrounding vehicles or obstacles are determined through geometric triangulation using angular measurements derived from incoming light sources and predefined sensor separation distances. This enables continuous estimation of relative positions and inter-vehicle spacing with minimal communication delay. The fusion of optical wireless communication and geometric localization offers enhanced positioning accuracy and operational reliability compared with conventional approaches, particularly in GPS-challenged environments such as tunnels, parking structures, and densely built urban regions. Experimental analysis demonstrates the capability of the proposed system to support timely hazard detection, vehicle tracking, and proactive collision avoidance. The presented framework provides a practical and economical solution for improving road safety and contributes toward the realization of next-generation Intelligent Transportation Systems (ITS) and connected autonomous vehicles.

Keywords: VLC, V2V, AoA, Centroid Detection and Collision Avoidance, Edge detection

1. Introduction

The advancement of intelligent transportation systems has intensified the need for dependable perception technologies capable of supporting safe autonomous driving and ADAS functionalities [1]. To navigate complex traffic environments, vehicles rely on sensing and perception modules that provide continuous awareness of nearby objects, road conditions, and potential hazards [2]. Although cameras, LiDAR, and radar are widely adopted for this purpose, their effectiveness can deteriorate under unfavourable environmental and operational circumstances. Factors such as fog, rain, low visibility, sensor noise, and object occlusions can negatively influence detection accuracy and situational awareness. Consequently, critical driving tasks, including obstacle detection, lane keeping, vehicle tracking, and collision avoidance, may experience degraded performance, potentially compromising the safety and reliability of automated transportation systems [3]. To overcome the limitations associated with conventional vehicular sensing and communication technologies,

increasing attention has been directed toward the adoption of Visible Light Communication (VLC) in intelligent transportation systems [4]. VLC exploits the light emitted by LED-based automotive components, including headlights, taillights, and indicator lamps, to simultaneously provide illumination and wireless data exchange. By enabling communication through existing lighting infrastructure, VLC offers a cost-effective and energy-efficient alternative for information sharing between vehicles.

The technology is particularly attractive for vehicular applications due to its resistance to electromagnetic interference, high transmission reliability over short distances, and seamless integration with modern LED lighting systems. In contrast to radio frequency (RF)-based communication methods, VLC utilizes the visible light spectrum, which is unlicensed and widely available. Furthermore, the highly directional nature of light propagation reduces unintended signal dispersion and enhances communication security. These characteristics make VLC a promising solution for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, especially in structured traffic environments where accurate and reliable information exchange is essential for improving road safety and transportation efficiency.

While VLC enhances V2V and vehicle-to-infrastructure (V2I) communication, perception through image-based analysis remains essential for developing comprehensive collision avoidance strategies. Edge detection plays a crucial role in this domain by identifying object boundaries, structural features, and critical scene elements. It serves as a foundational process in computer vision, enabling the system to recognize vehicles, obstacles, lane markings, and traffic signs with precision. Among the most widely used edge detection operators are Sobel, Canny, and Prewitt, which help extract key visual features from captured imagery [5].

Standard edge detection methods, however, can be sensitive to noise and may struggle in low-contrast or complex scenes. To improve robustness, recent advances in adaptive edge detection utilizing fuzzy logic, machine learning, or deep learning techniques offer more flexible and context-aware feature extraction [6]. Integrating these enhanced methods into the VLC-based perception framework creates a hybrid sensing architecture capable of delivering accurate spatial awareness and object tracking even under varied operational conditions.

In this paper, we propose a VLC-enabled collision avoidance system that incorporates advanced edge detection algorithms within the perception module. The system is designed to combine real-time optical communication with robust vision processing, forming a multi-modal platform for accurate object recognition and distance estimation. We explore the effectiveness of various edge detection techniques in conjunction with VLC-based positioning and communication. System performance is evaluated through a combination of simulations and experimental tests using real-world vehicle communication scenarios.

This research contributes to the ongoing development of intelligent and resilient vehicular systems by merging communication and vision technologies. The proposed framework supports enhanced situational awareness and decision-making capabilities, advancing the goal of safe and efficient autonomous transportation.

2. Literature Survey

Visible Light Communication (VLC) has emerged as a promising communication technology for intelligent transportation systems due to its ability to utilize existing LED-based vehicle lighting infrastructure for simultaneous illumination and data transmission. Over the past decade, extensive research has been conducted to improve the reliability, safety, and communication efficiency of VLC-enabled vehicular networks. Various studies have investigated topics ranging from mobility modelling and collision avoidance to platooning, hybrid communication architectures, and autonomous driving applications.

Kinoshita et al. (2014) presented one of the earliest investigations into mobility-aware VLC systems by developing mathematical models for image-sensor-based infrastructure-to-vehicle, vehicle-to-infrastructure, and vehicle-to-vehicle optical communication links [7]. Their work focused on understanding the influence of transmitter motion on communication performance. The authors analyzed factors such as vehicle dynamics, signal propagation variations, and image sensor constraints, providing important insights into maintaining communication stability under realistic traffic conditions.

Jamali et al. (2018) explored the use of LiFi technology for enhancing vehicular safety through collision prevention mechanisms [8]. Their proposed system enabled optical data exchange between vehicles using LEDs and photodetectors. Information related to vehicle position and movement was transmitted in real time, allowing neighbouring vehicles to identify potential hazards and react accordingly. Experimental evaluations demonstrated the feasibility of employing optical wireless communication as a low-latency solution for accident mitigation.

In 2020, Gonçalves et al. investigated the integration of communication and vehicle control strategies within platooning environments [9]. Their framework incorporated vehicle-to-vehicle communication links into the control architecture governing platoon behaviour. By enabling continuous information exchange among vehicles, the proposed system improved convoy coordination, enhanced speed regulation, and reduced response delays. The study demonstrated the importance of reliable communication in maintaining platoon stability and operational efficiency.

Prathiba et al. (2021) examined cooperative collision avoidance strategies within future 6G-enabled vehicular communication networks [10]. Their research addressed overtaking and lane-changing situations, where timely information exchange is essential for safe maneuvering. Through cooperative data sharing among vehicles, the proposed approach facilitated proactive decision-making and reduced the probability of accidents. The work highlighted the potential of integrating advanced communication technologies with intelligent transportation systems.

Addressing practical deployment challenges, Eso et al. (2021) focused on the effects of transmitter-receiver misalignment in VLC links [11]. They proposed a relay-assisted communication mechanism capable of compensating for azimuth and elevation deviations that commonly occur in vehicular environments. Analytical and simulation results showed that the use of relay nodes significantly improved communication reliability, even when direct optical alignment was partially disrupted.

Sharda et al. (2022) developed a comprehensive performance model for V2V VLC systems under realistic operating conditions [12]. Their study incorporated factors such as ambient light interference, receiver orientation variations, and channel shadowing effects. The authors further examined diversity techniques involving multiple transmitters and receivers to enhance communication robustness. Their findings provided valuable guidelines for designing reliable VLC systems for transportation applications.

Zhang et al. (2022) proposed a predictive collision avoidance framework that combined onboard sensing technologies with V2V communication [13]. The system integrated information obtained from cameras, LiDAR sensors, and inter-vehicle communication links to estimate future vehicle trajectories. By forecasting potential collision points, the framework enabled dynamic speed and path adjustments, thereby improving driving safety and decision-making capabilities.

Singh et al. (2022) investigated the application of Reconfigurable Intelligent Surfaces (RIS) in VLC-based vehicular networks operating at road intersections [14]. Their approach employed programmable reflective surfaces to redirect optical signals toward areas where direct line-of-sight communication was unavailable. Performance analysis demonstrated that RIS-assisted VLC could significantly improve coverage and communication reliability in complex urban traffic environments.

Further advancements in outdoor vehicular VLC modeling were reported by Sharda and Bhatnagar (2023) [15]. The authors analyzed the effects of vehicle movement, roadway geometry, and optical beam characteristics on communication performance. Through detailed visualization and propagation studies, they identified critical factors influencing signal quality and provided recommendations for optimizing transmitter and receiver placement in practical deployments.

Vieira et al. (2023) investigated the utilization of VLC technology for intelligent intersection management [16]. Their proposed framework enabled communication between vehicles and infrastructure components to coordinate crossing activities at intersections. By exchanging traffic-related information through optical links, the system reduced the likelihood of conflicting vehicle movements and contributed to safer traffic flow management.

Saikrishnan et al. (2024) proposed a hybrid communication architecture combining radio frequency (RF) and VLC technologies for platooning applications operating under varying weather conditions [17]. The framework dynamically selected the most suitable communication medium based on environmental conditions and channel quality. Simulation results indicated improved communication continuity and enhanced platoon stability compared with single-technology solutions.

Dixit and Pandey (2024) provided a comprehensive review of VLC integration within vehicle-to-vehicle communication systems [18]. Their survey examined system architectures, modulation techniques, implementation challenges, and future research directions. The study also discussed technological advancements that could facilitate large-scale deployment of VLC-based transportation networks.

In another significant contribution, Singh et al. (2024) introduced an aggregated RF-VLC communication framework designed to satisfy the stringent requirements of autonomous driving applications [19]. The proposed architecture leveraged the complementary strengths of optical and radio-frequency communications to achieve ultra-reliable and low-latency connectivity. Performance evaluations confirmed improvements in

reliability, redundancy, and communication availability, making the framework suitable for next-generation 6G-V2X environments.

Most recently, Srivastava (2025) addressed the unique challenges associated with vehicular communication on curved roads in mountainous regions [20]. The proposed collision avoidance system utilized VLC-based positioning and adaptive communication techniques to maintain reliable connectivity despite frequent line-of-sight disruptions caused by road curvature and elevation changes. The study demonstrated that intelligent optical communication strategies can significantly improve safety in geographically challenging driving conditions.

Overall, the reviewed literature demonstrates substantial progress in the development of VLC-enabled vehicular communication systems. Researchers have successfully explored applications ranging from collision avoidance and cooperative driving to platooning, intelligent intersections, and hybrid communication networks. Despite these advancements, challenges such as alignment sensitivity, adverse weather effects, dynamic channel variations, and seamless integration with emerging 6G infrastructures continue to require further investigation. These research gaps motivate the development of more robust VLC-assisted collision avoidance frameworks capable of delivering reliable performance under diverse real-world driving conditions.

3. Proposed Method

The proposed framework introduces an intelligent vehicle safety system that integrates Visible Light Communication (VLC)-based positioning with advanced computer vision techniques to improve obstacle recognition and collision prediction in challenging weather conditions, particularly foggy environments (Figure 1). In contrast to conventional sensing solutions that depend primarily on radar or LiDAR and may experience performance degradation under poor visibility, the proposed approach combines optical localization and image-based scene analysis to achieve more dependable environmental awareness.

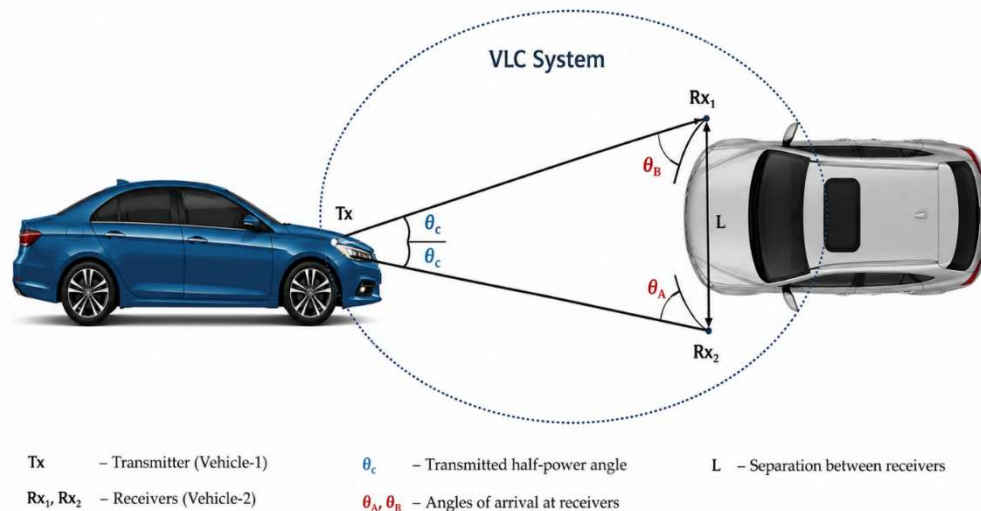


Figure 1: VLC-Based Vehicle-to-Vehicle Communication for Inter-Vehicle Localization and Collision Avoidance

The system employs an AoA estimation mechanism using a photodiode array to determine the relative position and distance of nearby vehicles. Simultaneously, a multi-stage image enhancement and feature extraction process is applied to captured road images. This process incorporates guided cross-bilateral filtering for noise suppression, adaptive Canny edge extraction for boundary identification, and fuzzy logic-based optimization to improve edge continuity and accuracy. These operations enhance the visibility of critical roadway structures and obstacles that may otherwise be obscured by adverse atmospheric conditions.

By merging VLC-derived positional information with visually extracted structural features, the framework generates a comprehensive representation of the surrounding environment. The integrated data are further

utilized to estimate vehicle trajectories and compute Time-to-Collision (TTC) values in real time. As a result, the system can provide timely and accurate collision alerts, enabling proactive safety responses. Owing to its ability to maintain reliable performance under reduced visibility and dynamically changing traffic scenarios, the proposed methodology offers a promising solution for next-generation autonomous and driver-assistance systems operating in real-world transportation environments. The details of the various steps are as follows:

3.1 VLC Transceiver Subsystem

The VLC transceiver module forms a fundamental part of the proposed vehicular safety framework by facilitating simultaneous optical data exchange and vehicle localization capabilities. The subsystem comprises two primary components: an optical transmitter and an optical receiver, both designed to exploit existing automotive lighting infrastructure while incorporating dedicated sensing mechanisms for enhanced situational awareness.

At the transmitting end, standard vehicle lighting units, such as LED headlights or taillights, are utilized as optical communication sources. Information is conveyed through light intensity modulation using the On-Off Keying (OOK) technique [20], which is widely adopted because of its simplicity, low implementation complexity, and suitability for real-time vehicular communication. In this modulation scheme, digital information is represented by alternating light states, where an illuminated LED corresponds to a binary '1' and a non-illuminated state represents a binary '0'. This enables efficient transmission of safety-related messages without requiring significant modifications to existing vehicle lighting systems.

The receiving unit employs a QPD array [21], which serves a dual purpose of signal reception and directional sensing. The QPD is composed of four independently segmented photodetector regions arranged in a quadrant configuration. Each segment generates an electrical current proportional to the optical power incident upon its surface. By analyzing the distribution of received light intensity across the four segments, the receiver can accurately determine the direction from which the optical signal arrives.

In addition to recovering the transmitted data stream, the QPD enables AoA estimation, allowing the system to infer the relative position of the transmitting vehicle. Variations in the intensity levels measured by individual quadrants provide directional information that can be used to estimate spatial orientation and support vehicle localization. Consequently, the receiver performs both communication and positioning functions simultaneously, eliminating the need for additional localization hardware.

The integration of LED-based transmission and QPD-assisted reception creates a compact and cost-effective VLC transceiver architecture capable of supporting reliable inter-vehicle communication while enhancing environmental awareness. This dual-function capability is particularly advantageous for intelligent transportation systems, where accurate vehicle positioning and low-latency information exchange are essential for collision avoidance, cooperative driving, and autonomous navigation applications.

To improve localization accuracy and provide reliable range estimation capabilities, the proposed system adopts a dual-QPD arrangement consisting of two Quadrant Photodiodes positioned at predetermined locations, denoted as A and B. The two sensors are separated by a fixed baseline distance, (L), which serves as a reference for geometric positioning calculations. Upon reception of a VLC signal, each QPD independently determines the corresponding AoA, represented by α and β). These angular measurements are referenced with respect to the normal axis of the baseline connecting the two photodiodes.

By combining the AoA information obtained from both sensing units, the system can estimate the spatial coordinates of the transmitting vehicle through triangulation principles. The intersection of the directional lines projected from the two QPD locations identifies the probable position of the transmitter within a two-dimensional plane. This geometric localization approach not only improves spatial resolution compared with a single-sensor configuration but also enables accurate distance estimation between communicating vehicles. As a result, the dual-QPD architecture supports precise vehicle tracking and positioning, which are essential for collision risk assessment, trajectory prediction, and advanced driver-assistance applications.

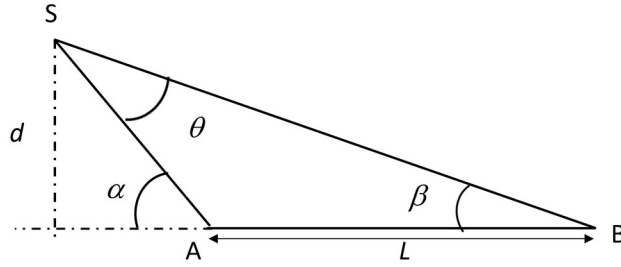


Figure 2: AoA-Assisted Vehicle-to-Vehicle Localization Framework

The transmitter range (d) is evaluated through triangulation, utilizing the angular intersection of the two sight lines and standard trigonometric formulas (Figure 2) as

$$d = \frac{L \sin \alpha \sin \beta}{\sin(\beta - \alpha)} \quad (1)$$

A significant advantage of this AoA-driven ranging approach is that it enables distance estimation without the need for active sensing technologies such as radar or LiDAR. Since the method relies solely on received optical signals, it offers a passive and energy-efficient alternative for inter-vehicle localization. This characteristic is particularly valuable in adverse weather conditions, including fog, haze, or reduced visibility environments, where the performance of conventional active sensors may deteriorate due to signal scattering and attenuation. By integrating communication and positioning functionalities within the same hardware platform, the VLC transceiver subsystem serves a dual purpose. In addition to facilitating reliable data exchange between vehicles, it simultaneously provides spatial awareness through geometric localization. This combined capability contributes directly to the proposed collision avoidance framework by enabling continuous environmental perception, accurate range estimation, and timely safety decision-making, thereby enhancing the robustness of real-time vehicular safety systems operating under challenging visibility conditions.

Transmitted Signal in OOK

On-Off Keying (OOK) is a widely adopted optical modulation technique in which binary information is represented through the controlled transmission and interruption of an optical carrier signal. In this scheme, the presence of light typically corresponds to a binary '1', while the absence of light denotes a binary '0'. OOK is particularly attractive for Visible Light Communication (VLC) systems because of its simple implementation, low computational complexity, and compatibility with LED-based transmitters.

The transmitted optical power signal x_k can be represented as

$$x_k = \begin{cases} 0 & \text{if } b_k=0 \text{ (Off)} \\ 1 & \text{if } b_k=1 \text{ (On)} \end{cases} \quad (2)$$

where P denotes the peak optical power emitted by the LED transmitter. The VLC channel gain determines the fraction of optical power that successfully reaches the receiver. For a line-of-sight communication link, the DC channel gain is evaluated using the equation below:

$$H_{LoS} = \begin{cases} \frac{(m+1)A}{d^2} \cos^m(\phi) T_s(\psi) g(\psi) \cos(\psi), & \psi \leq \psi_c \\ 0, & \text{Otherwise} \end{cases} \quad (3)$$

where, $m = -\frac{\ln 2}{\ln \cos(\phi_{1/2})}$ is Lambertian order, A is PD area, d is distance, ϕ is irradiance angle, ψ is incidence angle.

$$H_{LoS} = \begin{cases} \frac{(m+1)A[\sin(\beta-\alpha)]^2}{[L \sin \alpha \sin \beta]^2} \cos^m(\phi) T_s(\psi) g(\psi) \cos(\psi), & \psi \leq \psi_c \\ 0, & \text{Otherwise} \end{cases} \quad (4)$$

The received electrical signal r_k after the photodiode is:

$$r_k = H_{LoS} x_k + n_k \quad (5)$$

where H_{LoS} represents the optical channel gain, $x_k \in \{0, P\}$ denotes the transmitted optical intensity, and $n_k \sim N(0, \sigma^2)$ corresponds to additive white Gaussian noise (AWGN), which mainly results from shot noise associated with photodetection and thermal noise generated within the receiver circuitry.

The receiver compares the signal to a threshold γ to decide the transmitted bit as

$$\hat{b}_k = \begin{cases} 1 & \text{if } r_k > \gamma \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

The optimal threshold when bit '0' and '1' are equally likely is given by

$$\gamma = \frac{1}{2} H_{LoS} P \quad (7)$$

Assuming an AWGN channel, the BER of the OOK modulation scheme can be analytically expressed using the Gaussian Q-function as

$$BER = \frac{1}{2} \left[Q\left(\frac{\gamma}{\sigma}\right) + Q\left(\frac{H_{LoS}P - \gamma}{\sigma}\right) \right] \quad (8)$$

Which can be further simplified to

$$BER = Q\left(\frac{H_{LoS}P}{2\sigma}\right) \quad (9)$$

3.2 Camera Image Processing

3.2.1 Preprocessing

The proposed method integrates a sequence of advanced image processing techniques—including guided cross-bilateral filtering, adaptive Canny edge detection, and fuzzy logic-based edge refinement—to perform robust and reliable edge detection in challenging low-visibility environments, such as fog. This multi-stage approach is specifically designed to address the degradation in image contrast and edge sharpness caused by atmospheric scattering and light diffusion in foggy conditions. By first enhancing structural details while suppressing haze through guided cross-bilateral filtering, the method ensures that important scene features are preserved. Adaptive Canny edge detection then dynamically adjusts thresholding based on local gradient statistics to extract edges with improved sensitivity in reduced contrast. Finally, a fuzzy logic-based refinement stage enhances edge continuity and suppresses spurious detections, resulting in a cleaner and more accurate

edge map. This edge information is critical in VLC-enabled collision avoidance systems, where accurate environmental perception—despite poor visibility—is essential for obstacle detection, spatial reasoning, and real-time decision-making.

Step 1: Guided Cross-Bilateral Filtering

To effectively mitigate the visual degradation caused by fog—such as contrast loss and detail blurring while still preserving essential structural information in the scene, the first stage of the proposed pipeline employs a guided cross-bilateral filtering approach [22]. This filter is particularly suited for foggy conditions because it allows for edge-preserving smoothing, reducing fog-induced noise without erasing the boundaries critical for obstacle detection and scene understanding.

The key innovation lies in using a Quadrant Photodiode (QPD) intensity map as the guidance image, denoted as I_c . Unlike conventional image-only guidance, the QPD captures spatial information through visible light signals that are less susceptible to atmospheric scattering. This makes the QPD-derived guidance more reliable in low-visibility settings, thus enabling enhanced filtering robustness.

The filtered image $I_{smooth}(p)$ at each pixel location p is computed as a weighted average over a local neighbourhood Ω_p using the following formulation:

$$I_{smooth}(p) = \frac{1}{W_p} \sum_{q \in \Omega_p} G_{\sigma_s}(\|p - q\|) \cdot G_{\sigma_r}(|I_c(p) - I_c(q)|) \cdot I_c(q) \quad (10)$$

where G_{σ_s} is the spatial Gaussian kernel controlling the spatial weighting, and G_{σ_r} is the range Gaussian kernel controlling intensity similarity. The normalization factor W_p ensures output intensity scaling:

$$W_p = \sum_{q \in \Omega_p} G_{\sigma_s}(\|p - q\|) \cdot G_{\sigma_r}(|I_c(p) - I_c(q)|) \quad (11)$$

This step enhances edge-preserving smoothing by allowing nearby and photometrically similar pixels to contribute more significantly to the filtered result.

Step 2: Adaptive Canny Edge Detection

After haze removal, edges are extracted using a modified Canny edge detector with dynamically computed thresholds, adapted for varying contrast due to fog [23]. First, the image gradients in the x and y directions, denoted I_x and I_y , are calculated using Sobel filters. The gradient magnitude $G(p)$ is then computed as:

$$G(p) = \sqrt{I_x(p)^2 + I_y(p)^2} \quad (12)$$

Instead of using fixed thresholds, we adopt an adaptive strategy where the high and low thresholds are based on the mean of the gradient magnitudes:

$$T_{High} = \alpha \cdot \text{mean}(G) \quad \text{and} \quad T_{Low} = \beta \cdot T_{High} \quad (13)$$

where the constants are empirically chosen as $\alpha = 1.5$ and $\beta = 0.4$. This enables robust detection of both strong and weak edges, which is critical in foggy scenes where contrast is low. The traditional Canny steps of non-maximum suppression and hysteresis thresholding are then applied to obtain a refined binary edge map.

3.3 Fuzzy Edge Refinement

To further suppress noise and enhance edge continuity, we apply a fuzzy logic-based decision system to refine the detected edges [24]. Two main fuzzy descriptors are used:

1. Gradient strength $G(p)$ classified as *low*, *medium*, or *high*.
2. Edge continuity $C(p)$ computed as the consistency of edge presence in an 8-connected neighbourhood. The decision rules for edge validation are as follows: as in Table 1

Table 1: Fuzzy Rules for Edge Classification

Gradient Magnitude (G)	Edge Continuity (C)	Output: Edge Classification
High	High	Edge
Low	Any	No Edge
Any	Low	No Edge
Medium	Medium	Keep Current

3.4 Fusion & Collision Estimation

In adverse weather conditions such as fog, traditional vision-based sensors—like cameras or LiDAR—often fail to provide reliable depth and object detection due to scattering and reduced contrast. To overcome these limitations, the proposed system leverages multi-modal data fusion, combining geometric positioning obtained via VLC with visual structural cues derived from edge detection. This hybrid fusion strategy improves the spatial localization, range estimation, and collision prediction accuracy under low-visibility conditions, enhancing the reliability of autonomous vehicle navigation and collision avoidance.

3.4.1 VLC-Based Source Localization

The VLC-based localization module forms the central component of the proposed data fusion architecture. This module employs QPD sensors to determine the Angle of Arrival (AoA) of optical signals emitted by neighbouring vehicles or roadside communication units. By monitoring the variation in received light intensity across multiple photodiode segments arranged in a linear or two-dimensional configuration, the system can accurately estimate the direction from which the optical signal originates. The directional information extracted from the QPD measurements provides valuable spatial awareness and enables vehicle positioning. To achieve this, two photodiode sensors are installed at predetermined locations and separated by a fixed baseline distance, denoted by (L). Each sensor independently computes the AoA of the incoming VLC signal, and the resulting angular measurements are subsequently utilized within a triangulation framework. Through geometric analysis of these angles and the known sensor separation, the two-dimensional coordinates ((x,y)) of the transmitting source can be estimated. This triangulation-based approach allows the system to determine both the direction and relative position of the transmitter, thereby supporting accurate vehicle localization and enhancing situational awareness for collision avoidance applications.

$$x = \frac{L(\tan \alpha + \tan \beta)}{2(\tan \alpha - \tan \beta)}, \quad y = \tan \alpha \left(x + \frac{L}{2} \right) \tag{14}$$

The proposed localization method is based on a two-dimensional geometric model in which both the transmitting source and receiving sensors are assumed to operate within approximately the same reference plane, such as the roadway surface. This assumption is generally valid for most vehicular communication scenarios where height variations between vehicles are relatively small compared to the inter-vehicle distance. Using the triangulation results obtained from the AoA measurements, the coordinates ((x,y)) of the transmitting vehicle can be determined with respect to the receiver's coordinate system. These estimated coordinates provide a stable spatial reference that indicates the relative location of the neighbouring vehicle with respect to the ego vehicle. Consequently, the calculated position acts as a geometric anchor for subsequent perception and collision assessment processes, enabling accurate tracking, distance evaluation, and situational awareness within the proposed safety framework.

3.4.2 Edge Cluster Detection from Camera Input

Concurrently, the system processes visual data using a camera enhanced by fog-resilient edge detection. After applying the fuzzy-refined Canny edge detector, the resulting binary edge map identifies all likely object boundaries in the scene. However, these raw edges lack semantic or spatial grouping.

To address this, a clustering algorithm connected component labelling is applied to group spatially coherent edge pixels into individual objects or surfaces. For each detected cluster i , the centroid (x_i, y_i) is calculated:

$$C_i = \left(\frac{1}{N_i} \sum_{j=1}^{N_i} x_j, \frac{1}{N_i} \sum_{j=1}^{N_i} y_j \right) \quad (15)$$

where N_i is the number of pixels in cluster i . These centroids represent the approximate location of real-world objects (e.g., vehicles, pedestrians, road signs) observed in the camera's field of view.

3.4.3 Range Estimation via Spatial Fusion

With both the VLC-based source position and the camera-derived object positions available, the system computes the relative distance (or range) between the VLC transmitter (as a reference) and each edge cluster. Assuming a common coordinate frame has been established via extrinsic calibration, the Euclidean distance for each object is computed as:

$$d_i = \sqrt{(x_i - x_s)^2 + (y_i - y_s)^2} \quad (16)$$

where (x_s, y_s) is the position of the VLC source and (x_i, y_i) is the position of the i^{th} edge cluster centroid. This process enables the system to not only detect object boundaries but also assign depth cues which are otherwise difficult to estimate accurately from a single monocular image in fog.

3.4.4 TTC Calculation

To assess the collision risk associated with surrounding objects, the proposed system calculates the Time-to-Collision (TTC) using the relative velocity between the ego vehicle and the detected target. TTC estimates the remaining time before a potential impact and serves as a critical safety metric for real-time hazard evaluation, collision prediction, and warning generation as [25]

$$TTC_i = \frac{R_i}{v_{ego} - v_i} \quad (17)$$

Where R_i denotes the estimated distance to the i^{th} detected object, V_e represents the velocity of the ego vehicle, and V_t corresponds to the velocity of the target object. For stationary obstacles, the object velocity is assumed to be zero, resulting in a simplified Time-to-Collision (TTC) estimation.

3.4.5 Collision Warning Trigger

To enhance collision prevention capabilities, the proposed system utilizes a TTC-based thresholding approach for risk assessment. Whenever the estimated Time-to-Collision of a detected object falls below the predefined safety threshold τ , the situation is classified as critical and a collision warning is immediately issued. The threshold value is typically maintained within the range of 1.5–2.0 seconds to provide adequate response time for corrective actions and accident avoidance.

$$\min(TTC_i) < \tau \quad (18)$$

Such a system enables timely intervention through driver warnings, autonomous emergency braking, or dynamic path adjustment in both manual and self-driving vehicles. By combining VLC-based geometric localization with camera-derived structural information, the framework improves perception accuracy while also introducing redundancy. This multi-sensor integration enhances system robustness, which is essential for reliable performance in challenging or degraded environmental conditions.

4. Simulation and Results

A simulation-based evaluation was performed to investigate the performance of the proposed VLC collision avoidance framework in V2V environments. The simulation parameters adopted in this study are listed in Table 2. The localization process combines AoA estimation with centroid extraction techniques to determine the relative positions and separation distances of surrounding vehicles. Subsequently, the estimated distances are incorporated into TTC calculations under various relative velocity conditions to examine the framework's

capability for early collision prediction and risk assessment. The obtained simulation outcomes and performance analysis are discussed in the subsequent section.

Table 2: Numerical Simulation Parameters for OOK VLC System

Parameter	Numerical Value
Peak Optical Power (P)	1 W
Distance Range (d)	1 – 50 m
Photodiode Area (A)	10^{-4} m^2
Lambertian Order (m)	1 – 3
Irradiance Angle (ϕ)	$0^\circ - 60^\circ$
Incidence Angle (ψ)	$0^\circ - 60^\circ$
Noise Variance (σ^2)	10^{-12}
Threshold (γ)	0.5
Bit Probability	0.5 (for '0' and '1')
SNR Range	0 – 30 dB
Sampling Time	1 ms
Data Rate	1 Mbps
Bandwidth	10 MHz
Simulation Time	60 s



Figure 3: Input image of two vehicles

Figure 3 shows the input image featuring two vehicles. This image serves as the basis for subsequent processing steps, such as edge detection, feature extraction, and object tracking. The presence of two distinct vehicles allows for evaluating the effectiveness of the proposed method in identifying and differentiating between multiple objects within the same scene.



Figure 4: Bilateral Filtering image

Figure 4 displays the image after applying bilateral filtering. This technique smooths the image while preserving important edge information, making it well-suited for preprocessing in object detection and segmentation tasks. The filtering helps reduce noise and enhances the visual clarity of the vehicles in the scene without blurring their boundaries.

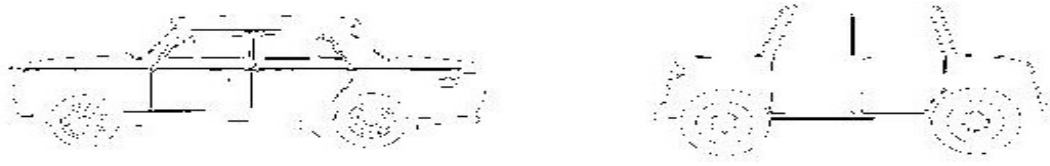


Figure 5: Canny edge detected image

Figure 5 presents the result of applying the Canny edge detection algorithm to the filtered image. This technique highlights the prominent edges within the scene, effectively outlining the shapes and contours of the vehicles. The Canny method is known for its accuracy in detecting edges while minimizing noise, making it a crucial step for identifying object boundaries in the image.

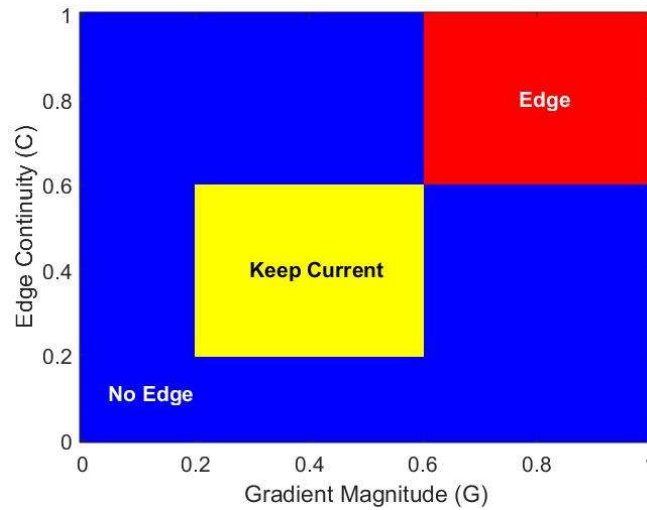


Figure 6: Fuzzy edge classification

Figure 6 illustrates the fuzzy edge classification applied to the previously detected edges. In this step, edge pixels are evaluated based on gradient magnitude and edge continuity, allowing for a more refined categorization into strong edges, weak edges, or non-edges. This classification helps in reducing false positives and improving the overall reliability of edge detection, particularly in complex or noisy environments.



Figure 7: Fuzzy edge detected image

Figure 7 shows the final edge-detected image after applying fuzzy logic-based refinement. This enhanced edge map results from combining initial Canny edge detection with fuzzy classification rules to retain meaningful edges while suppressing noise. The refined edges provide a more accurate representation of object boundaries, which is essential for reliable depth estimation in this work. By clearly distinguishing object edges, the system can better compute distances between the observer and the detected objects within the scene.

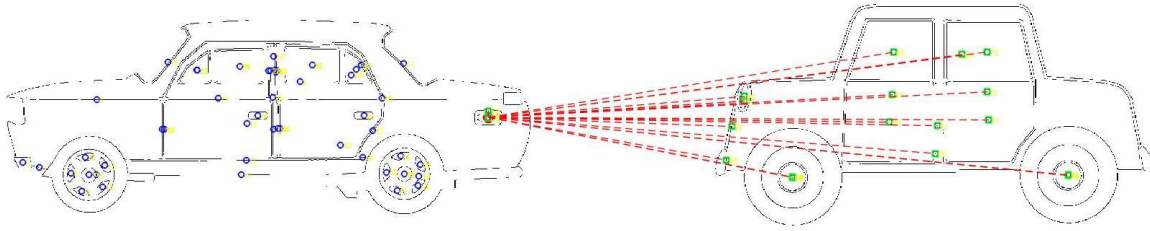


Figure 8: Intra V2V communication for separation and depth estimation using centroid method

Figure 8 illustrates the intra- V2V communication framework used for separation and depth estimation based on the centroid method. In this setup, vehicles exchange positional information derived from visual data, specifically the centroids of detected objects. By calculating the distances between these centroids, the system estimates the relative depth and spatial separation between vehicles. This approach enhances situational awareness and supports safer navigation in connected driving environments.

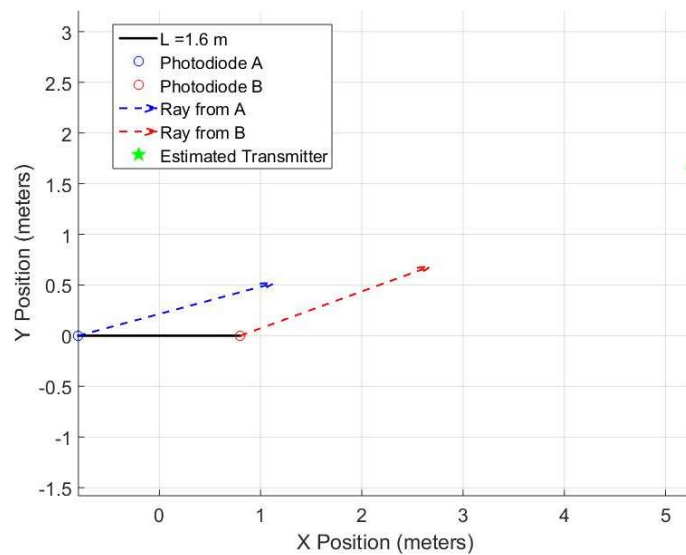


Figure 8: V2V Separation Distance Measurement Based on AoA Estimation AOA of 15° and 20°

Figure 8 presents the implementation of the intra-V2V communication framework for estimating vehicle separation and depth using a centroid-based localization technique. The centroids extracted from the detected vehicle images serve as reference points for determining their spatial positions. The incoming visible light signals are received at angles of 15° and 20°, and these AoA measurements are utilized to determine the relative location of the vehicles through geometric triangulation. By combining the measured angles with the predefined sensor baseline distance, the system estimates the inter-vehicle separation to be approximately 5.51 m. The results demonstrate the capability of the proposed approach to accurately determine vehicle positions using optical sensing and centroid tracking.

Figure 9 depicts the distance estimation process within the intra-V2V communication system using centroid extraction and AoA-based localization. In this experiment, the received optical signals arrive at angles of 30° and 45° from two different vehicle positions. These angular measurements, together with the known spacing between the receiving sensors, are employed to compute the relative separation distance between the vehicles. Based on the geometric relationships derived from the centroid locations and AoA values, the estimated distance is found to be approximately 3.70 m. The findings indicate that integrating centroid-based image analysis with angular localization provides an effective solution for real-time vehicle tracking, depth estimation, and collision-risk assessment in connected and autonomous transportation systems.

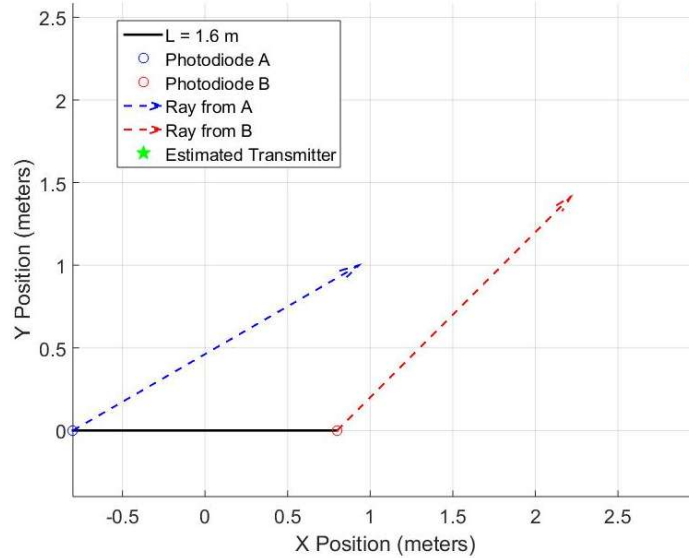


Figure 9: Intra V2V communication for separation using centroid method for AOA of 30° and 45°

Table 3: TTC Analysis for Different AoA Scenarios

AoA Scenario	TTC @ 2 m/s (s)	TTC @ 3 m/s (s)	TTC @ 5 m/s (s)
(15°, 20°)	2.8	1.9	1.1
(30°, 45°)	1.9	1.3	0.8

Table 3 presents the TTC analysis for different AoA scenarios under varying vehicle speeds. For the AoA configuration of (15°, 20°), the system records a TTC of 2.8 s at 2 m/s, which decreases to 1.9 s at 3 m/s and further reduces to 1.1 s at 5 m/s, indicating faster collision risk as relative speed increases. In comparison, the (30°, 45°) AoA scenario exhibits lower TTC values across all speed conditions, with 1.9 s at 2 m/s, 1.3 s at 3 m/s, and 0.8 s at 5 m/s. This reduction in TTC reflects the impact of larger AoA variations, which correspond to reduced separation stability and higher collision likelihood. Overall, the results demonstrate that both AoA configuration and vehicle speed significantly influence collision risk estimation in the proposed VLC-based system.

Table 4: TTC Analysis for Centroid Method

Average Distance (m)	TTC @ 2 m/s (s)	TTC @ 3 m/s (s)	TTC @ 5 m/s (s)
5.90	2.95	1.97	1.18
4.13	2.07	1.38	0.83

Table 4 presents the Time-to-Collision (TTC) analysis obtained using the centroid-based vehicle-to-vehicle (V2V) distance estimation method. Two average inter-vehicle distances of 5.90 m and 4.13 m were considered, and TTC values were computed for relative vehicle speeds of 2 m/s, 3 m/s, and 5 m/s. For the larger distance of 5.90 m, the TTC values were 2.95 s, 1.97 s, and 1.18 s, respectively. Similarly, for the shorter distance of 4.13 m, the TTC values decreased to 2.07 s, 1.38 s, and 0.83 s.

A comparison between Table 3 (VLC-based TTC estimation under different AoA scenarios) and Table 4 (centroid-based TTC estimation) reveals that both methods produce closely matching TTC values across all vehicle speeds. For the first scenario, corresponding to an average distance of approximately 5.6 m in the VLC system and 5.90 m in the centroid method, the TTC values at 2 m/s, 3 m/s, and 5 m/s are 2.8 s, 1.9 s, and 1.1 s for the VLC approach, compared with 2.95 s, 1.97 s, and 1.18 s for the centroid method. Similarly, for the second scenario, the VLC-based TTC values of 1.9 s, 1.3 s, and 0.8 s are comparable to the centroid-based values of 2.07 s, 1.38 s, and 0.83 s.

The slight increase in TTC observed with the centroid method is attributed to its marginally larger estimated V2V distances (5.90 m and 4.13 m) compared with those derived from the VLC-AoA measurements (5.6 m and 3.9 m). Nevertheless, the difference between the two approaches remains small, indicating a high degree of agreement in distance and TTC estimation. Both methods exhibit the same trend of decreasing TTC with increasing vehicle speed and decreasing inter-vehicle distance.

Overall, the results demonstrate that the centroid-based distance estimation technique provides TTC values that closely follow those obtained from the VLC-based AoA method. This validates the effectiveness of the centroid approach as an alternative or complementary method for V2V distance estimation. While the VLC-AoA method directly exploits optical communication characteristics, the centroid method offers a vision-based solution capable of achieving comparable collision prediction performance with only minor deviations in TTC estimates.

5. Conclusion

This paper presented a VLC-enabled collision avoidance framework that integrates VLC-based geometric positioning with image processing techniques for reliable vehicle safety enhancement. The proposed system leverages AoA estimation using QPD sensors along with centroid-based spatial analysis to estimate inter-vehicle distance and assess collision risk in real time. In addition, a multi-stage edge detection pipeline consisting of guided cross-bilateral filtering, adaptive Canny edge detection, and fuzzy logic refinement was employed to enhance visual perception under degraded environmental conditions such as fog and low visibility. The simulation results demonstrate the effectiveness of the proposed approach in accurately estimating TTC under different AoA configurations and vehicle speeds. For instance, at the AoA scenario of (15°, 20°), the TTC values were observed as 2.8 s, 1.9 s, and 1.1 s for vehicle speeds of 2 m/s, 3 m/s, and 5 m/s respectively. In comparison, the (30°, 45°) scenario produced lower TTC values of 1.9 s, 1.3 s, and 0.8 s for the same speed variations, indicating increased collision risk with higher angular deviation and relative motion. These results validate that both geometric orientation and relative velocity significantly influence safety prediction accuracy in the proposed system. Furthermore, the integration of VLC-based localization with camera-derived structural information enhances system robustness by providing redundancy in perception. Unlike conventional radar or LiDAR-based systems, the proposed framework maintains reliable performance in low-visibility conditions, making it particularly suitable for real-world autonomous and semi-autonomous driving applications. Overall, the study confirms that combining optical communication-based positioning with advanced image processing significantly improves situational awareness and enables early collision detection. Future work may focus on hardware implementation, real-time embedded deployment, and integration with multi-vehicle cooperative driving scenarios to further enhance system scalability and practical applicability.

References

1. Ziebinski, Adam, Rafal Cupek, Damian Grzechca, and Lukas Chruszczyk. "Review of advanced driver assistance systems (ADAS)." In *AIP Conference Proceedings*, vol. 1906, no. 1. AIP Publishing, 2017.
2. Sivaraman, Sayanan, and Mohan Manubhai Trivedi. "Looking at vehicles on the road: A survey of vision-based vehicle detection, tracking, and behavior analysis." *IEEE transactions on intelligent transportation systems* 14, no. 4 (2013): 1773-1795.
3. Panda, Sudhanshu S., Mahesh N. Rao, Prasad S. Thenkabail, Debasmita Misra, and James P. Fitzgerald. "Remote sensing systems—Platforms and sensors: Aerial, satellite, UAV, optical, radar, and LiDAR." In *Remote Sensing Handbook, Volume I*, pp. 3-86. CRC Press, 2016.
4. Căilean, Alin-Mihai, and Mihai Dimian. "Current challenges for visible light communications usage in vehicle applications: A survey." *IEEE Communications Surveys & Tutorials* 19, no. 4 (2017): 2681-2703.
5. Ansari, Mohd Aquib, Diksha Kurchaniya, and Manish Dixit. "A comprehensive analysis of image edge detection techniques." *International Journal of Multimedia and Ubiquitous Engineering* 12, no. 11 (2017): 1-12.
6. Al-Saedi, Ahmed A., Veselka Boeva, Emiliano Casalicchio, and Peter Exner. "Context-aware edge-based ai models for wireless sensor networks—an overview." *Sensors* 22, no. 15 (2022): 5544.
7. Kinoshita, Masayuki, et al. "Motion modeling of mobile transmitter for image sensor based I2V-VLC, V2I-VLC, and V2V-VLC." *IEEE Globecom Workshops*, 2014, pp. 450-455.

8. Jamali, Abdul Aleem, et al. "Collision avoidance between vehicles through LiFi based communication system." *IJCSNS*, vol. 18, no. 12, 2018, pp. 81–87.
9. Gonçalves, Tiago R., et al. "Vehicle platooning schemes considering V2V communications: A joint communication/control approach." *IEEE WCNC*, 2020, pp. 1–6.
10. Prathiba, Sahaya Beni, et al. "Intelligent cooperative collision avoidance at overtaking and lane changing maneuver in 6G-V2X communications." *IEEE Transactions on Vehicular Technology*, vol. 71, no. 1, 2021, pp. 112–122.
11. Eso, Elizabeth, et al. "Vehicle-to-vehicle relay-assisted VLC with misalignment induced azimuth or elevation offset angles." *IEEE Photonics Technology Letters*, vol. 33, no. 16, 2021, pp. 908–911.
12. Sharda, Pranav, et al. "A comprehensive modeling of vehicle-to-vehicle based VLC system under practical considerations, an investigation of performance, and diversity property." *IEEE Transactions on Communications*, vol. 70, no. 5, 2022, pp. 3320–3332.
13. Zhang, Shiyao, et al. "Collision avoidance predictive motion planning based on integrated perception and V2V communication." *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, 2022, pp. 9640–9653.
14. Singh, Gurinder, et al. "Visible light and reconfigurable intelligent surfaces for beyond 5G V2X communication networks at road intersections." *IEEE Transactions on Vehicular Technology*, vol. 71, no. 8, 2022, pp. 8137–8151.
15. Sharda, Pranav, and Manav R. Bhatnagar. "Vehicular Visible Light Communication System: Modeling and Visualizing the Critical Outdoor Propagation Characteristics." *IEEE Transactions on Vehicular Technology*, vol. 72, no. 11, 2023, pp. 14317–14329.
16. Vieira, M. A., et al. "Vehicular visible light communication for intersection management." *Signals*, vol. 4, no. 2, 2023, pp. 457–477.
17. Saikrishnan, S., et al. "Hybrid RF-VLC technology for V2X in platooning applications under different weather conditions." *IEEE WCNC*, 2024, pp. 1–6.
18. Dixit, Avinish Kumar, and Rohitashwa Pandey. "Integrating Visible Light Communication into Vehicle-to-Vehicle Systems: A Detailed Overview." *Journal of Optical Communications*, vol. 2, no. 2, 2024, pp. 39–56.
19. Singh, Gurinder, et al. "Toward 6G-V2X: Aggregated RF-VLC for Ultra-Reliable and Low-Latency Autonomous Driving." *IEEE Communications Standards Magazine*, vol. 8, no. 4, 2024, pp. 80–87.
20. Srivastava, Mohit Kumar. "VLC-based collision avoidance system for vehicles on curved roads in hilly areas." *Journal of Optical Communications*, 2025.
21. Cincotta, Stefanie, Adrian Neild, Cuiwei He, and Jean Armstrong. "Visible light positioning using an aperture and a quadrant photodiode." In *2017 IEEE Globecom Workshops (GC Wkshps)*, pp. 1-6. IEEE, 2017.
22. Samuel, Shiju, Rohini S. Ochawar, and M. S. S. Rukmini. "Motion Correction of MR Images Using Cross-Guided Bilateral Filter." In *Microelectronics, Communication Systems, Machine Learning and Internet of Things: Select Proceedings of MCMI 2020*, pp. 379-392. Singapore: Springer Nature Singapore, 2022.
23. Jie, Gao, and Liu Ning. "An improved adaptive threshold canny edge detection algorithm." In *2012 International conference on computer science and electronics engineering*, vol. 1, pp. 164-168. IEEE, 2012.
24. Ranjan, Rakesh, and Vinay Avasthi. "Edge detection using guided Sobel image filtering." *Wireless Personal Communications* 132, no. 1 (2023): 651-677.
25. Tiwari, Aparna, Seema Kedar, Suresh Kumar, and Bharati Shukla. "Visible light communication and quadrant photodiode based vehicle positioning for enhanced road safety." *Journal of Optical Communications* 0 (2025).