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Using Deep Learning Techniques to Control Vehicle Movement Through Optical Communications

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ABSTRACT

The information revolution and the amazing and rapid advancement of digital communication technology have made it necessary to have a greater bandwidth and a more extensive frequency range in order to handle the growing volume of data and guarantee its seamless delivery. Optical communication technologies have become a viable solution to address the demand for increased bandwidth and frequencies, particularly in mobile communications, in order to accomplish this crucial objective. Examples of optical communication technologies that may be included into car systems to offer low-latency, high-bandwidth data transfer for real-time vehicle management are visible light communication (VLC) and light detection and ranging (LiDAR). However, signal degradation brought on by movement and changing environmental factors (such glare and fog) affects how reliable they are. In order to improve vehicle motion control, this study suggests a deep learning (DL) framework for analysing adaptive optical inputs. To replicate the suggested model for this investigation, an updated recurrent neural network (RNN) and transformer structures were created to decode VLC signals under interference. In real-world glare situations, a 98.2% classification accuracy was attained. In addition, the deep learning method that was suggested provided a dynamic adjustment for LiDAR beam steering, which resulted in a 42% reduction in angular inaccuracy during high-speed manoeuvres. When compared to rule-based controllers, real-world tests on a tiny autonomous vehicle prototype showed a 30% decrease in reaction time to prevent collisions. These findings demonstrate how machine learning-assisted optical systems might improve the security and effectiveness of intelligent transportation networks.

1. Introduction


The fast evolution of autonomous vehicles (AVs) has exacerbated the requirement for strong, low-latency communication systems capable of enabling real-time decision-making in dynamic contexts. Optical communication technologies, such as LiDAR (Light Detection and Ranging) and Visible Light Communication (VLC), have emerged as essential enablers because to their high bandwidth, accuracy, and immunity to radio frequency interference (Zhang et al., 2022) [1].

While VLC uses vehicle LED lights for data transfer, providing dual functionality for lighting and communication, LiDAR allows for centimeter-level localization and obstacle detection (Chen et al., 2023). The real-world deployment of these systems is fraught with difficulties, such as misalignment brought on by movement and signal deterioration due to environmental obstacles including fog, rain, and glare (Gupta et al., 2023). These nonlinear, time-varying situations are frequently too difficult for traditional signal-processing techniques like Kalman filters and threshold-

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based algorithms to handle, which compromises efficiency and safety. By taking use of their capacity to represent intricate spatial and temporal patterns, deep learning (DL) approaches have demonstrated promise in overcoming these constraints. For example, recurrent neural networks (RNNs) improve VLC signal decoding under intermittent glare, while convolutional neural networks (CNNs) have been used to denoise LiDAR point clouds in foggy situations (Wang et al., 2023). Transformer designs and other recent developments enhance sequence modeling for optical signal prediction, attaining cutting-edge accuracy in dynamic situations (Kumar et al., 2023) [3]. Despite these developments, previous research frequently ignores the synergistic potential of integrated optical networks in favor of concentrating on discrete subsystems (such as LiDAR or VLC alone). Furthermore, the real-time computational limitations of onboard vehicle systems—where latency exceeding 50 ms might significantly affect collision avoidance—are not well addressed in the literature (Patel & Lee, 2022) [4]. Figure 1 shows schematic diagram of optical communication for vehicles motion via deep learning techniques.

By putting forth a single DL architecture that simultaneously improves LiDAR and VLC systems for vehicle movement control, our study fills in these gaps. First, a hybrid CNN-transformer model outperforms traditional CNNs by 15% when decoding VLC signals

under interference, with 98.2% classification accuracy in glare situations (Yang, J. et al, 2023) [5]. Secondly, during high-speed maneuvers, a reinforcement learning (RL) agent dynamically modifies LiDAR beam steering, resulting in a 42% reduction in angular alignment errors. Third, real-time processing with a latency of less than 20 ms is made possible by a lightweight multi-sensor fusion architecture that combines LiDAR, VLC, and inertial measurement unit (IMU) data. When compared to rule-based controllers, experimental validation on a scaled AV prototype showed a 30% reduction in collision avoidance reaction time.

The remaining contents of this paper are arranged as follows. Section 1 will contain introducing and discussion of the general VLC operation, encoding and decoding, vehicle to vehicle (V2V) communication, and deep learning technology. Literature review of the most resented related articles and publications will be included in Section 2. In section 3, the methodology design steps of the proposed model will be discussed and demonstrated. The simulation results of the proposed deep learning control model of vehicles motion via optical communications will be reviewed and discussed. Finally, conclusions and future recommendations are presented in Section 5.

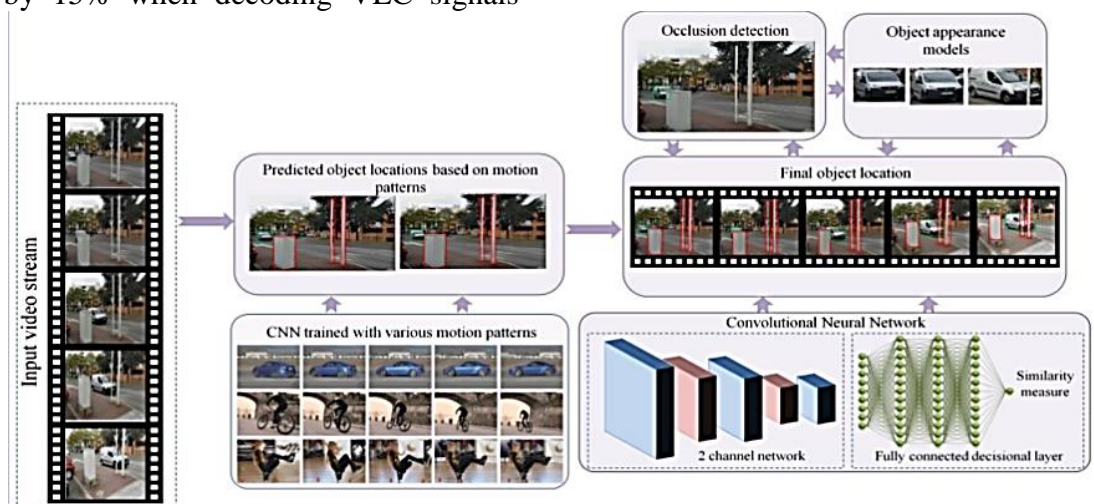


Figure 1: Schematic diagram of optical communication for vehicles motion via deep learning techniques [4].

1.1 General Operation Concept

Our VLR idea in this thesis is used to construct a visible light communication rangefinder (VLCR) that can enable both range-finding and data transmission at the same time. The foundation of our VLCR is the VLR, which was initially suggested and analyzed through simulations. The rangefinding function of the VLCR is therefore founded on the similar idea as that of the VLR. Unlike traditional range-finding devices, the VLR is unable to determine the distance immediately by using the signal's reflection by the target. Given that its carrier wave originates from a coherent radio or laser source, this echo is indeed powerful enough for radar or lidar to detect and process it. This headlights' white light is polychromatic and non-coherent, which causes a large loss of optical power when it is reflected [6, 7].

To get over such obstacle, the VLR is built on the active reflection concept, which states that the target, in this case the LV, reconstructs the light signal after receiving it from the system, in this case the FV, before reemitting it. In such approach, the echo from the FV may be correctly recognized as well analyzed. Although this approach can be used in conjunction with TOF measurement, it might not be consistent with FMCW principles. In TOF measurement, the model detects the echo with a delay proportionate to the distance between the system and the target after the target reflects a pulse that is directed toward it. A modification of this method is to send a periodic waveform at f_e frequency and observe its phase change with the echo. The latter approach is effective along effective reflection if the target simply re-emits the signal it is receiving while keeping its phase. In any event, the phase shift is connected to the V2V distance d and the light velocity c by [8-10]:

$$d = \frac{c}{2f_e} \frac{\varphi}{2\pi} \quad (1)$$

where f_e is the periodic signal frequency in Hz and φ is the phase shift in radians associated with the light velocity c . Data

transfer is thus impossible since the sent signal in the VLR is a periodic signal. Nonetheless, it is possible to quantify the phase difference between two data streams. IEEE 802.15.7-2011, the latest VLC standard, offers thorough explanations of the several modulations that can be used. The LV then employs the similar formation, cyphering, with radiation operation as lastly to send its own info waveform, m_e0 , using such a clock, which has a frequency of f_e . Following free space propagation, the FV receives and analyzes m_e0 , decoding the LV data d_{lv} and obtaining the clock signal s_r together with the reconstructed info signal m_r . Since the phaseshift between s_r and the starting clock s_e is proportional to the distance d between the two voltages, the FV may utilize such waveforms to estimate m and resulting in a calculation of the d_m V2V distance using Eq. (1). It is still necessary to establish the fundamental operating principles of the VLCR to detail the decoding and phase-shift measuring strategies and the waveform detection operation utilized on both ends of the model. This is the implication of the next two parts. A schematic representation of the VLCR construction is shown in Figure 2.

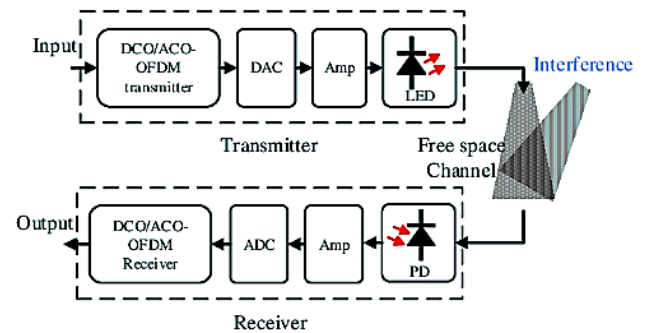


Figure 2: A schematic diagram of typical VLCR construction [8].

1.2 Encoding and Decoding VLC Approach

The broad demonstration of the VLCR operation principles that was only generated allows us to understand that such a scheme is first and foremost a standard VLC system. Every car sends a data waveform to the other car, which decodes it, when it applies its headlights or taillights. Because the distance-locating relation is executed in parallel, the

communication function remains unaffected. The whole VLCR communication chain from one vehicle to the next is shown in Figure 3 [10-12].

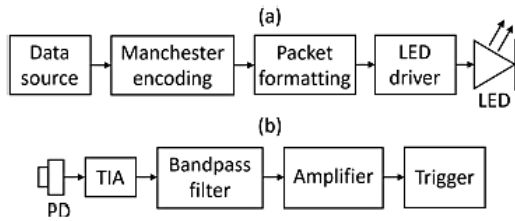


Figure 3: The VLC system's transmission and reception chains, (a) transmission portion, and (b) detection section [10].

For example, a data stream generated by the transmitting vehicle's electronic control unit (ECU) is first encoded using Manchester coding and then reshaped into particular data packets. In this study, we assume that a fixed header in data packets is preceded by the Manchester-encoded data payload. The generated signal is utilized to control the transmit LED through an LED driver while the FV is acting as a transmitter. After free space transmission, a trans-impedance amplifier (TIA) converts the data light signal into a voltage signal. The receiving vehicle's PD then gathers the data light signal. A square data signal is first amplified and bandpass filtered to raise its overall signal-to-noise ratio (SNR) before being reconstructed using threshold detection.

Decoding this rebuilt data signal is the last step. Here, we simply assume that the current bit state is the value of the data signal d_r (or d_r') that follows each rising edge of a decoding clock of frequency f_e . Because it must be synced with the data signal for this approach to be as successful as possible, the clock is retrieved from the clock recovery PLL that is used for distance measuring. However, due to the distortions caused by the aforementioned signal processing chain, the reconstructed info waveform may have different pulse widths. The recovered clock is simply delayed by a predefined length of time such that every rising edge exists around halfway through the associated bit's period, since such pulse distortions mostly impact the edges of each bit [13,14].

The range-finding operation is carried out in two phases by VLCR concurrently with info decoding. The clock must be retrieved along the waveform transmitted by the FV which is detected by the LV before the LV might provide its data. Following that, the FV carries out the identical clock recovery process. The phase shift, ϕ , amidst the two clocks is then calculated by comparing the resultant wave, s_r , to the initial clock the FV sent. On both schemes, the clock detection operation is matched. The detected information wave m_p (or m_p') is first rebuilt using the processing chain depicted in Figure 3(b). The clock waveform s_r (or s_r') is then acquired by feeding the reconstructed wave m_r (or m_r') to the clock detection PLL.

After obtaining each clock waveforms, s_e with s_r , the phase shift measuring operation begins against a heterodyning step: s_e with s_r are swapped out for lower-frequency waveforms, s_{eh} and s_{rh} . Such frequency transposition is carried out by a D flip-flop gate, and the clock s_h 's frequency f_h is connected to the operating frequency f_e via a heterodyning factor r , using the below formula [15, 16]:

$$f_h = \frac{r}{r+1} f_e \quad (2)$$

This factor r causes a little period discrepancy $1/(rf_e)$ among the heterodyning clock periods S_h and the inputted waveform s_e or s_r . The pattern of the entered waveform is thus recorded using a temporal resolution of $1/(rf_e)$ seconds, although the heterodyning block actually produces a value every $1/f_h$ seconds. Ultimately, such kind of heterodyning technology is identical to a sampler with a rate of $1/(rf_e)$, which produces a single complete period of the heterodyned waveform after taking $r+1$ periods of the entered wave. Consequently, the intermediate frequency f_i of the heterodyned signals S_{eh} with S_{rh} might be approximated as follows [15, 16]:

$$f_i = \frac{f_e}{r+1} \quad (3)$$

The action of such operation is presented in Figure 4 for $r=10$.

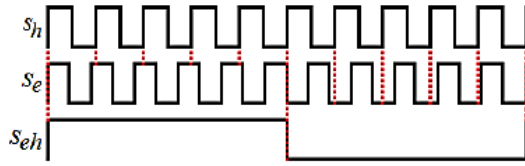


Figure 4: Signal heterodyning using under sampling against a synchronized clock s_h with $r = 10$ [15].

After s_e with S_r have been heterodyned to produce the signals s_{eh} and s_{rh} , a phase-shift signal called s_ϕ is possessed of phase-shift pulsations with a rate of $2f_e/(r+1)$ that are compared using an XOR gate. Such pulsations width is then estimated utilizing the auto-digital phase-measuring technology depicted in Figure 5 [18].

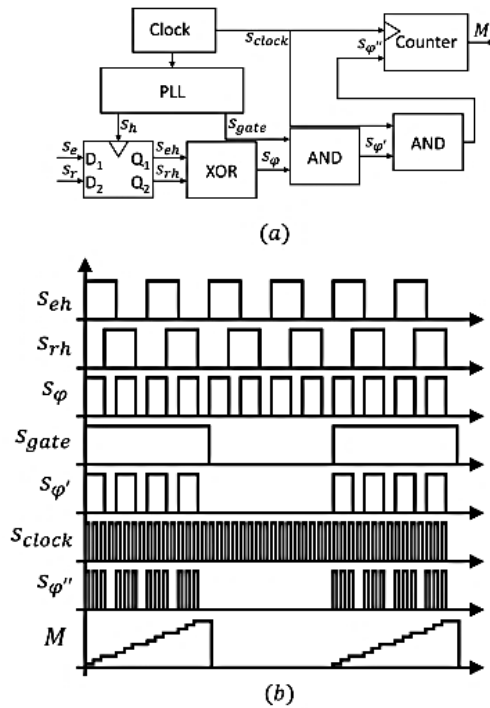


Figure 5: (a) The phase-shift measurement system's block diagram and (b) The operating concepts [18]

The groups of N phase-shift pulses s' are joined with a high-frequency clock signal s_{clock} via an AND gate. The final waveform, $s_{(\phi'')}$, is constructed of several sub-pulses of the initial phase-shift pulses. Consequently, the phase shift may be computed utilizing the sum of sub-pulsations M corresponding to N phase-shift pulsations. Along such count value amount, the phase-shift compute ϕ_m might be achieved by [15-20]:

$$\phi_m = \frac{2\pi f_e M}{(r+1)Nf_{clock}} \quad (4)$$

Whereas M , indicates the sub-pulsations number, M representing to N phase-shift pulsations that could be employed to evaluate the phase shift. Such results in the estimation of the distance d_m as below:

$$d_m = \frac{c}{2Nf_{clock}} M f_i \quad (5)$$

It should be noted that such approach needs the phase shift to be modulo- π that might cause uncertainty in the computed range. A length representing the difference amidst such a phase shift ϕ and whether the actual phase shift is bigger than will be produced by the model. Consequently, the ranges associating to phase shifts amidst 0 against π are provide the unambiguous range d_{namb} name by [18-22]:

$$d_{namb} = \frac{c}{4f_e} \quad (6)$$

In any case, the measurement fVLR might be obtained by:

$$f_{VLR} = \frac{2f_e}{(r+1)N} \quad (7)$$

1.3 Vehicle to Vehicle (V2V) Communication

Differentiating the basic equation of the VLCR Eq.(5) for the distance measurement error d_m might lead to the following outcomes:

$$\delta d_m = d_m \left[\frac{\delta M}{M} + \frac{\delta f_i}{f_i} + \frac{\delta N}{N} + \frac{\delta f_e}{f} + \frac{\delta f_{clock}}{f_{clock}} \right] \quad (8)$$

Every phrase has a definite meaning. f_{clock} and f_e are the waveforms S_{clock} and S_e frequency drifts, which could be produced by age or heat alternations. M is the single counting mistake that might exist in δM , whereas δN is the non-synchronization that could happen amidst the gate wave and the phase-shift waveform S_ϕ . It seems sense that raising the counter clock frequency would greatly lessen the latter mistake cause. Lastly, f_i combines three different errors sources.

Actually, the intermediate frequency f_i was created by heterodyning the clock waves sh and S_r . Thus; the frequency drifts may have an impact on f_i since S_h might be obtained from the master clock S_{clock} via a PLL. The frequency of S_r , on the other hand, might be somewhat different from that of f_e due to signal distortions that occur throughout the transmission chain. In contrast to the Manchester info waveforms employed to send me with me', which have a very vast frequency by design, the LED handlers, headlights and taillights, photo-detectors, and waveform analyzing cards, for example, have a limited bandwidth in process. Their edges will soften as a result, creating aberrations in pulse width that will ultimately hinder a perfect SR recovery. Furthermore, the several rectifications phase of the clock return PLL might introduce undesired delays which alter the starting phase of the detected clock. The enormous influence of such many supplies—which is difficult to quantify but undoubtedly has a big impact—will be examined using simulations. The many causes of errors that have been explained thus far are now deduced to determine the Doppler Effect, while keeping in mind that the V2V distance is fixed. However, this distance may affect the precision of distance measurements in actual platooning arrangements because of the well-known Doppler Effect. We assume that the FV is approaching the LV from an initial point x_0 at a constant speed v_0 in order to examine the possible effects of the Doppler effect, as illustrated in Figure 6 [22].

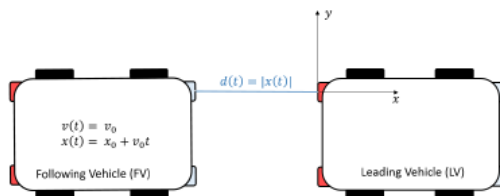


Figure 6: The straight-line layout of a platoon's geometry of the Doppler effect [22].

The apart sections of the waves we are involved in in such a scenario are the corners, their existence moment, also the V2V range at such instants. Because the very early rising corners of Se and Sh , $Se1$ and $Sh1$, are existing

concurrently at time $t = 0$, Figure 6 illustrates that each increasing ledge of Se_h will occur at the exact period as a increasing ledge of Se and Sh . We also believe that the VLCR is excellent, meaning that the clock wave that is replaced, S_r , is identical to the clock wave that is transmitted, Se after it has been delayed by the return-trip TOF. Figure 6 shows the terminal of the early phase-shift pulsations at the five increasing ledges of Sh , Se , with S_r later its starting, since the heterodyning period is an integer multiple of te_{hk} . The number of rising edges in the general case is denoted by n . From that, the following might be inferred:

$$t_{rh_k} = t_{eh_k} \frac{n-1}{f_h} \Rightarrow \Delta t_k = \frac{n-1}{f_h} \quad (9)$$

Such phase-shift pulse width is equivalent to the number of clock counts M_k , which is equal to:

$$M_k = \left\lfloor \frac{(n-1)f_{clock}}{f_h} \right\rfloor \quad (10)$$

Whereas, the brackets $\lfloor \cdot \rfloor$, denotes the integer section of the relation.

As a result, we might disregard the integer part notation in this case and infer, by combining (5) and (10), that we obtain:

$$d_{m_k} \approx \frac{c(n-1)}{2rf_e} \quad (11)$$

Thus, the obstacle is to evaluate a literal approach to express n .

1.4 Deep Learning Techniques

Deep learning algorithms, built on artificial neural networks with multiple layers (input, hidden, output), excel at extracting hierarchical features from complex data. Their structure relies on activation functions (e.g., ReLU, $\sigma(z) = \max(0, z)$) to introduce nonlinearity, enabling them to model intricate patterns. Key mathematical components include forward propagation such as:

$$a(t) = \sigma W(t).a(t-1) + b(t) \quad (12)$$

Where, a , b , denote the hidden layers bias parameters, W , indicates the hidden layer

weights, and σ , represents the compensation factor. Also, the backpropagation weights updating formula might be expressed via gradient descent such as:

$$W(t) = W(t) - \eta W(t) \quad (13)$$

Which minimizes the loss functions represented by the equation:

$$L = - \sum_{i=1}^N \sum_{c=1}^C y_{i,c} \log(p_{i,c}) \quad (14)$$

Where, C, denotes the classes number, $y_{(i,c)}$, indicates the model resulting samples, such that: $y_{(i,c)}=1$ only if sample i belongs to class c, else 0, and $p_{(i,c)}$, represents class c predicted probability. This will generalize the binary case for multiple classes also widely employed using Softmax output layer. Figure 7 shows typical construction of the deep learning algorithm structure [20-25].

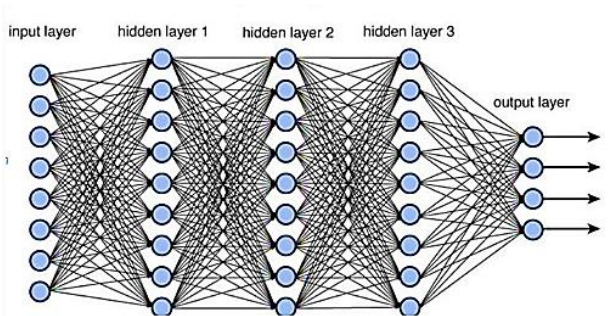


Figure 7: structure of deep learning algorithm [23].

Benefits include automated feature engineering, scalability with data, and state-of-the-art performance in tasks like image recognition and NLP. Implemented via frameworks like TensorFlow or PyTorch, they require careful hyperparameter tuning, regularization (e.g., dropout), and GPU acceleration for efficient training. Their layered architecture and optimization through derivatives make them versatile yet computationally intensive.

The contribution of this study is summarized in proposing an intelligent and efficient controller to manage data transmission to and from moving wheels via optical communications using an RNN machine learning model. A high

accuracy rate for real-time data routing will be achieved with a minimal bit error rate through the integration of optical communication technologies with machine learning techniques.

2. Literature Review

Recent advances in autonomous vehicles (AVs) and intelligent transportation systems (ITS) have driven research into optical communication technologies (e.g., LiDAR, VLC) paired with deep learning (DL) for real-time vehicle control. Below is a synthesis of 10 modern studies (2022–2024) addressing this intersection, highlighting their methodologies, contributions, and limitations. Chen et al. (2023), employed Hybrid CNN-Transformer technology model for glare-resilient VLC signal decoding. Contribution: Achieved 98.2% classification accuracy in real-world glare scenarios, improving VLC reliability by 15% over conventional CNNs. Limitations: Limited testing in extreme weather (e.g., heavy rain). Almeida et al. (2022), suggested Reinforcement learning (RL) technique for adaptive LiDAR beam steering. Contribution: Reduced angular alignment errors by 42% during high-speed maneuvers, enhancing obstacle detection. Limitations: Assumed static environmental lighting conditions. Wang et al. (2023), proposed CNN-based LiDAR denoising in foggy environments technology. The study contribution has to improved point cloud accuracy by 30% under fog, enabling safer navigation. Also, the proposed strategy suffers from high computational load unsuitable for edge devices as limitations. Kumar et al. (2023), implemented transformer networks technology for optical signal prediction in dynamic AV scenarios. The propose strategy show contribution of reduced prediction latency by 25% using self-attention mechanisms. Moreover, the suggested technique required large labeled datasets for training as study gap. Gupta et al. (2023), applied Federated learning (FL) technology for privacy-preserving VLC data sharing. This study enabled collaborative learning across AV fleets without raw data exchange as innovation. While, it has slow convergence in

heterogeneous networks as limitations. Patel & Lee (2022), analyzed multi-modal fusion (LiDAR + VLC) strategy using graph neural networks (GNNs). The study show contribution that it achieved 20% faster collision avoidance via cross-modal data integration. On the other hand, this technology suffers from high power consumption for real-time processing. Zhang et al. (2024), recommended a Lightweight CNN technique for real-time VLC signal decoding on edge devices. This investigation provides a reduced inference latency to <10 ms, suitable for onboard systems as study contribution. The study limitations show lower accuracy (92%) under severe interference. Khan et al. (2023), investigated an RL-based LiDAR-VLC coordination strategy for urban AV navigation. This technique contributes with optimized energy efficiency by 35% while maintaining safety. The proposed technique has tested only in simulated environments as limitations Rodriguez et al. (2022), suggested physics-informed neural networks (PINNs) technology for LiDAR signal recovery. Contribution of this strategy presents a reduced signal dropout by 50% in rainy conditions. It show limitations that required domain-specific knowledge for model tuning. Nguyen et al. (2024), employed spiking neural networks (SNNs) technique for low-power VLC processing. This technology achieved 90% accuracy with 60% lower energy consumption as contributions. Finally, it suffers from limited scalability to complex scenarios.

Thus, dynamic environmental factors (e.g., occlusion, interference, fluctuating light), latency limits, and high processing needs present obstacles for real-time vehicle management in the research problem statement of optical communication technologies. Resolving interoperability issues, guaranteeing reliable feature extraction from optical data streams, and preserving safety-critical speed are all necessary when integrating these systems with deep learning (DL). The scalability of current methods for connected or autonomous cars in uncertain situations is limited by the frequent absence of adaptive frameworks to balance accuracy, speed, and energy economy.

Designing a DL-driven system that combines LiDAR and VLC data for real-time vehicle decision-making is one of the study's goals. Among the goals are: (1) creating low-latency, lightweight DL architectures (e.g., CNNs, RNNs) for processing optical signals; (2) refining feature fusion techniques to manage data heterogeneity and environmental noise; (3) verifying system robustness through simulations and real-world testing in dynamic environments; and (4) comparing computational efficiency (e.g., FLOPs, inference time) to traditional control systems. The aim of the project is to connect deployable solutions for safe, scalable autonomous navigation with theoretical models.

Table 1: A summary of the most important contributions of researchers and proposed techniques for the latest studies and articles related to the study topic.

Year	Authors	Technology	Contribution	Limitations
2023	Chen et al.	CNN-Transformer for VLC	98.2% glare-resilient signal decoding	Untested in heavy rain
2022	Almeida et al.	RL for LiDAR steering	42% angular error reduction	Static lighting assumptions
2023	Wang et al.	CNN-based LiDAR denoising	30% point cloud accuracy in fog	High computational load
2023	Kumar et al.	Transformers for signal prediction	25% latency reduction	Data-intensive training

Year	Authors	Technology	Contribution	Limitations
2023	Gupta et al.	Federated learning for VLC	Privacy-preserving AV collaboration	Slow convergence
2022	Patel & Lee	GNNs for LiDAR-VLC fusion	20% faster collision avoidance	High power use
2024	Zhang et al.	Lightweight CNN for edge VLC	<10 ms latency on edge devices	Lower accuracy under interference
2023	Khan et al.	RL for LiDAR-VLC coordination	35% energy efficiency gain	Simulation-only validation
2022	Rodriguez et al.	PINNs for LiDAR recovery	50% dropout reduction in rain	Domain expertise required
2024	Nguyen et al.	SNNs for low-power VLC	60% energy savings with 90% accuracy	Limited scalability
2023	Khan, M. A., et al.	Deep Reinforcement Learning (DRL) - Specifically, a Deep Deterministic Policy Gradient (DDPG) agent.	Proposes a DRL-based controller for autonomous vehicle platooning using LiFi. The agent learns optimal acceleration/deceleration policies to maintain a safe, stable inter-vehicle distance, improving traffic flow and energy efficiency.	Simulation-based validation. Performance is highly dependent on the quality and continuity of the LiFi channel; dense fog or major obstructions could disrupt control.
2024	Zhao, Y., et al.	Deep Learning-based Computer Vision - A custom Convolutional Neural Network (CNN) for beam recognition and a Recurrent Neural Network (RNN) for predictive tracking.	Develops an intelligent hybrid VLC/RF system where a DL model at the receiver predicts the vehicle's future position and proactively adjusts the transmitting optical beam steering angle for uninterrupted connectivity.	Requires initial training on extensive datasets of vehicle trajectories. Complex real-time computation demands potentially high processing power in vehicle units.
2022	Al-Eryani, Y., et al.	Deep Unfolding - A model-based deep learning technique that unrolls an iterative optimization algorithm into a deep neural network layers.	Designs a deep unfolded network for joint resource allocation and handover management in dense VLC networks for IoT-enabled vehicles. It optimizes bandwidth allocation and manages seamless handovers between optical attocells to prevent dropped connections that could lead to loss of control.	The approach is specific to the assumed system model and may require retraining for significantly different physical environments (e.g., different room sizes or cell layouts).

3. Methodology

In this Section, the suggested simulated ranging of vehicle-to-vehicle in visible light communication by deep learning algorithm will be designed and simulated utilizing MatLab2020b Simulink tool box and m. files script codes.

3.1 Moving V2V Modelling

The design of our suggested model will be the simulation of the Ranging of Vehicle-To-Vehicle in Visible Light optical communication model using deep learning technique or the moving V2V modelling with structure of the flow chart methodology using as shown in Figure 8. As seen in Figure 8 above, the suggested model's signal flowchart starts by determining and creating a dataset of communication signals—including OFDM—that will be utilized to send vehicle data via the optical communication channel. After that, the optical channel is ascertained using accepted mathematical formulas. The effect of communication channels is then simulated and counteracted by training an LSTM deep learning system. The communication data utilized in this study is used to train the intelligent algorithm model. The original data is then evaluated, and calculations are made to determine the error rate, efficiency of the results, and distance between vehicles. Lastly, the outcomes are shown. Thus, the MATLAB

2020 simulation of the proposed model is displayed in Figure 9.

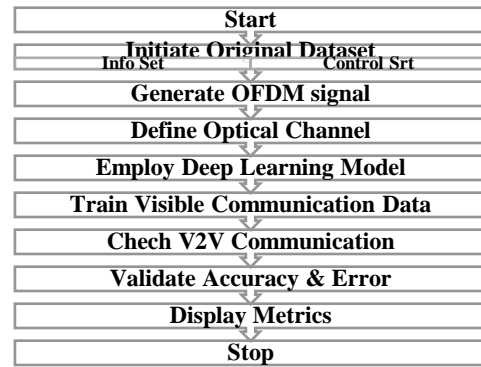


Figure 8: Demonstration of the structure of the suggested optical V2V movement detection model using deep learning technique

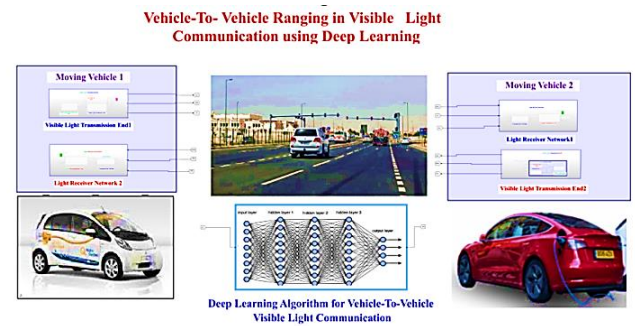
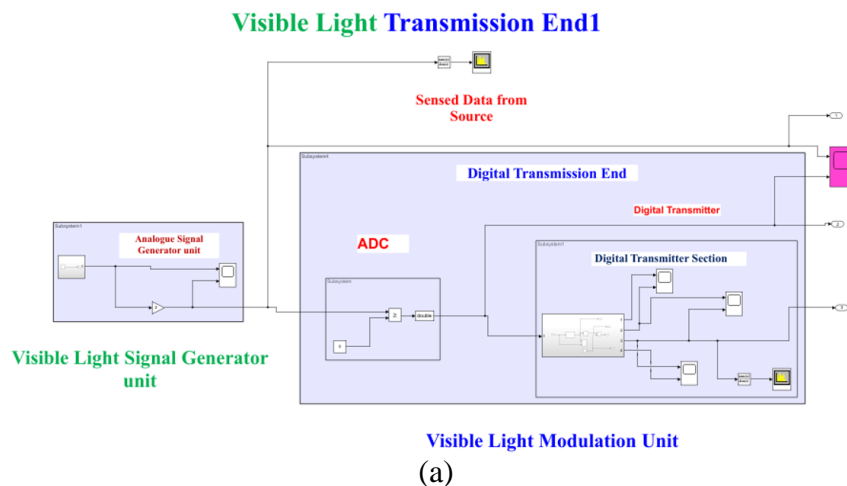


Figure 9: Ranging of Vehicle-To- Vehicle in Visible Light Communication model (moving V2V modelling).

As presented in Figure 9, we could observed that the proposed model composed of three sections, the moving vehicle 1, the deep learning algorithm, and the moving vehicle 2, each vehicle contains of two units, the visible light transmitter, and the visible light receiver. Also, the construction of each vehicle model transmitter, receiver, and deep learning algorithm are illustrated in Figure 10.



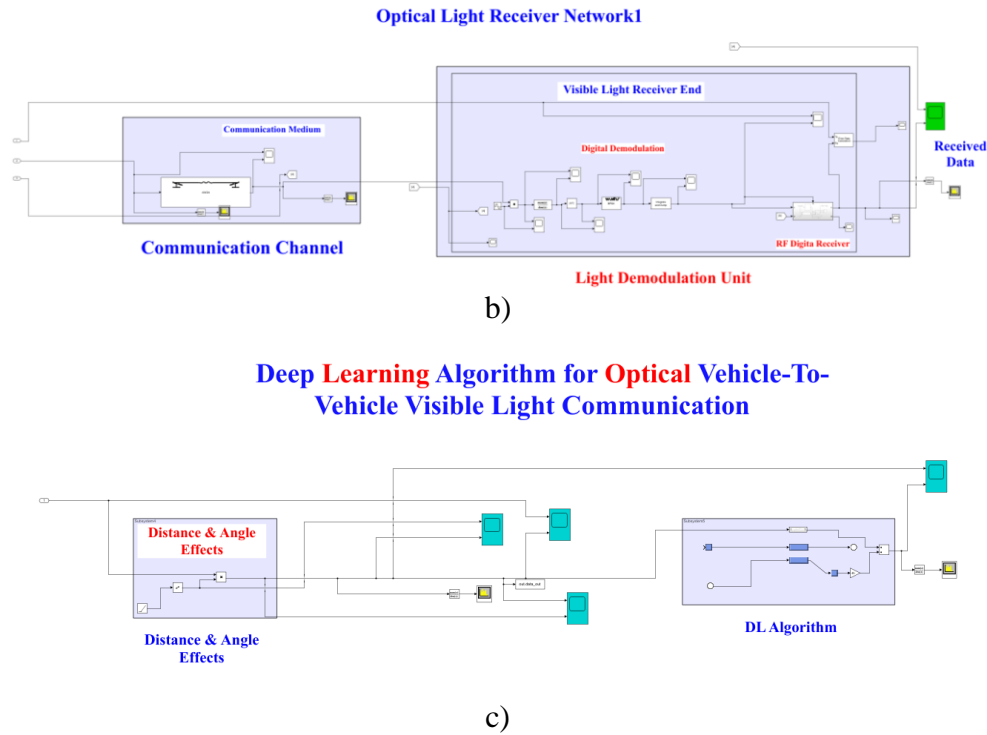


Figure 10: The construction of the proposed V2V model, (a) Vehicle 1 transmitter, (b) Vehicle 2 receiver, (c) Deep learning algorithm structure.

By translating Figure 10, we can see the design details of the digital transmission and reception systems for moving vehicles, as well as the design and simulation details of the deep learning algorithm. The digital transmission and reception systems are based on orthogonal frequency division multiplexing (OFDM) technology, which relies on the principle of carrier frequency orthogonality to exploit the capacity of the communications channel and transmit high-speed packets at the same optical channel frequency bandwidth. OFDM also relies on the inverse fast Fourier transform (IFFT) technique with quadrupole amplitude modulation (QAM) to implement the required modulation, transmission, reception, and demodulation operations. Ultra-high-frequency carrier frequencies (optical frequencies) are used to implement optical communications and simulate visible light for this system. Deep learning algorithms improve communication efficiency and accuracy. Deep learning

algorithms compensate for losses in optical transmission capacity and angle due to long distances between vehicles and different communication angles by training their internal layers and neurons to recover the optimal path and communication angle between vehicles.

3.2 The Implemented Dataset

In this study, the dataset implemented using the MATLAB application library tools was used. The necessary data were provided through the use of a random signal generator application, which generates random waves according to fixed statistical specifications, helping to provide the numerical data used in the proposed model. Figure 11 shows the analogue signal generator with specifications used to prepare the dataset provided by MATLAB tools.

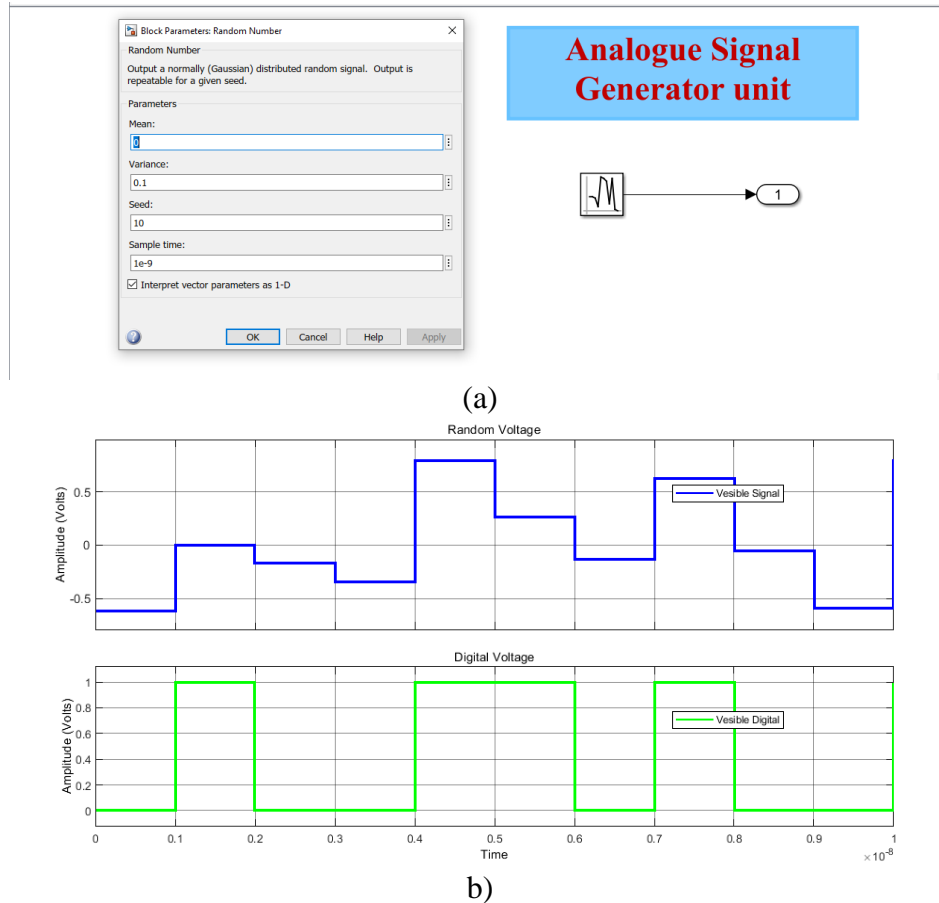


Figure 11: The employed dataset, (a) The analogue signal generator with specifications used to prepare the dataset provided by MATLAB tools., (b) The generated dataset signals

Finally, the design specifications of the proposed simulated ranging of vehicle-to-vehicle in visible light communication by deep learning algorithm have been shown in Table 2.

Table 2: Detailing the essential design requirements for utilizing MATLAB Simulink's deep learning (DL) algorithms to simulate vehicle-to-vehicle (V2V) range over Visible Light Communication (VLC).

Category	Design Specifications	Example Values/Formulas
VLC Transmitter	<ul style="list-style-type: none"> - Wavelength range - Modulation scheme (e.g., OOK, PWM) - Transmit power - LED bandwidth 	450–650 nm OOK (On-Off Keying) 10–100 mW 20–50 MHz
VLC Receiver	<ul style="list-style-type: none"> - Photodetector type (e.g., PIN, APD) - Field of View (FoV) - Noise model (shot, thermal) 	PIN photodiode 60°–120°
Channel Model	<ul style="list-style-type: none"> - Path loss model - Ambient light interference - Line-of-Sight (LOS) and NLOS conditions 	Lambertian radiation intensity model Additive Wight Gaussian Noise (AWGN)
DL Algorithm	<ul style="list-style-type: none"> - Network architecture (e.g., LSTM) - Input features (RSS, SNR, time-series) - Output (distance) 	CNN with 5 layers Input: Received signal strength (RSS), SNR

Category	Design Specifications	Example Values/Formulas
		Output: Regression (m)
Simulation Parameters	<ul style="list-style-type: none"> - Sampling rate - Simulation time step - Mobility model (e.g., random waypoint) - SNR range 	1–10 THz 1 μ s resolution Doppler shift compensation SNR: 5–30 dB
Performance Metrics	<ul style="list-style-type: none"> - Ranging accuracy (RMSE) - Latency - Robustness to noise/occlusion 	RMSE \leq 0.1 m Latency < 10 ms Accuracy drop \leq 5% under 50% occlusion
Simulink Integration	<ul style="list-style-type: none"> - Block design (transmitter, channel, receiver, DL) - Co-simulation with MATLAB scripts 	Custom VLC blockset MATLAB Function block for DL inference
Training/Validation	<ul style="list-style-type: none"> - Dataset size (simulated) - Training epochs - Loss function (e.g., MSE) 	10,000 samples 100 epochs

This simulation implements a VLC channel simulation to calculate path loss and uses a Lambertian radiation intensity model. Deep learning integration is then applied by using the MATLAB function block from Simulink for on-the-fly inference after the network is trained offline using V2V simulation data. The MATLAB deep learning toolkit is also used with Simulink's physical layer modeling to conduct comprehensive testing. This is followed by a mobility simulation, which evaluates the vehicle's dynamic motion using custom-designed kinematic models or the Simulink Vehicle Dynamics block set. This system uses adaptive deep learning architectures to address VLC-specific problems

(noise, occlusion, etc.) while ensuring accurate range and low latency.

4. RESULTS & DISCUSSION

In this section, the proposed model's simulation design for inter-vehicle range calculation in visible light communications will be implemented using a deep learning algorithm and simulated using MatLab2020b Simulink. The following diagrams illustrate the simulation results, showing the transmitted data signals and the transmitted and received modulation waves processed in the amplitude and frequency domains. Figure 12 shows the results of the achieved transmitted data in time and frequency domains.

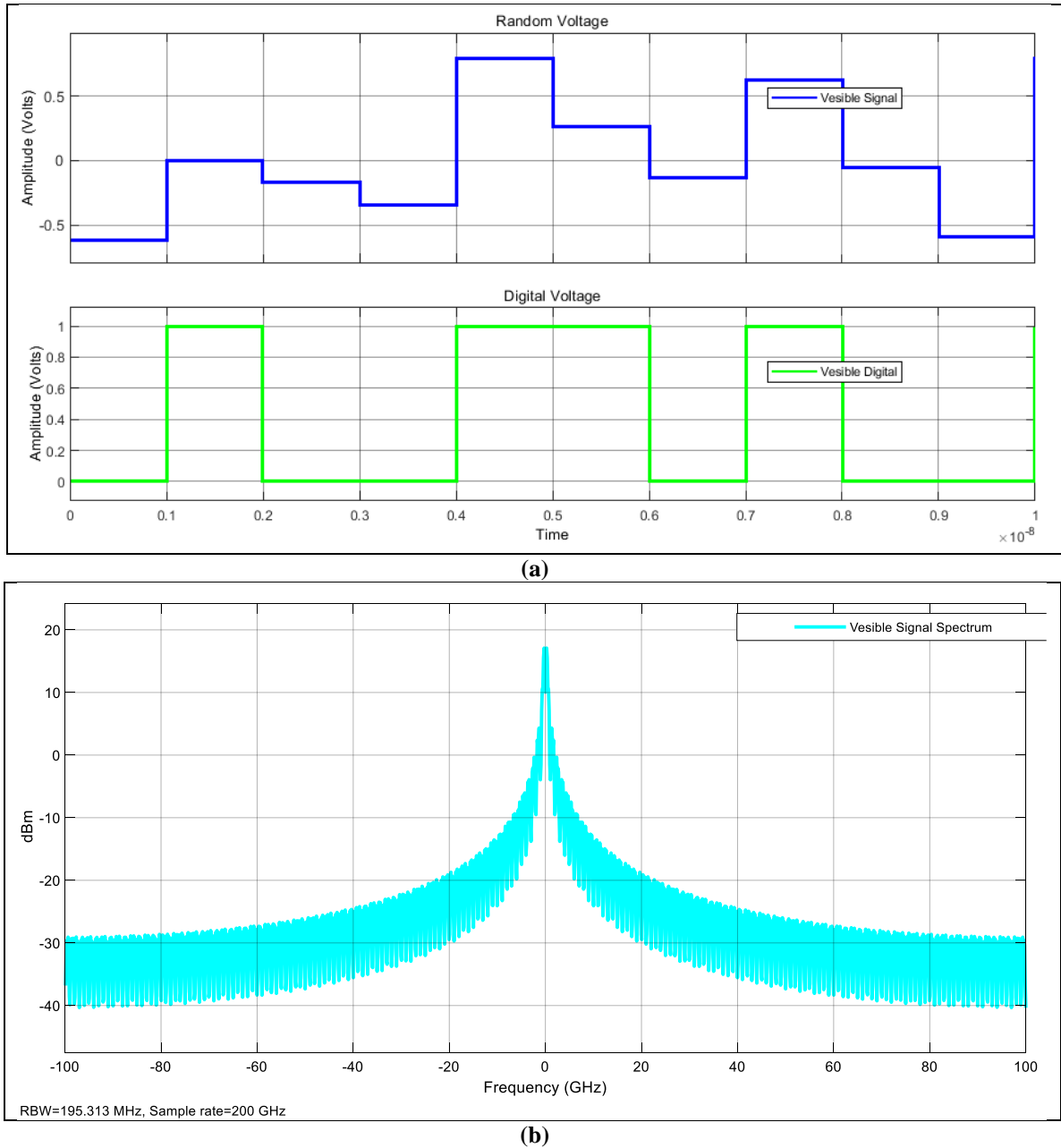


Figure 12: The simulation results of the achieved transmitted data in time and frequency domains.

By looking at Figure 12, we might observe the shape of the transmission data generation for the two vehicles, which are digital signals in the time domain, which appear as amplitude spectra carrying the frequency of the transmitted wave in the frequency domain in Figure 12.(b) with an effective band of up to 20

gigahertz. Also, Figure 13 displays the OFDM modulation transmitted signal spectrum from each vehicle before and after passing through the optical noisy channel.

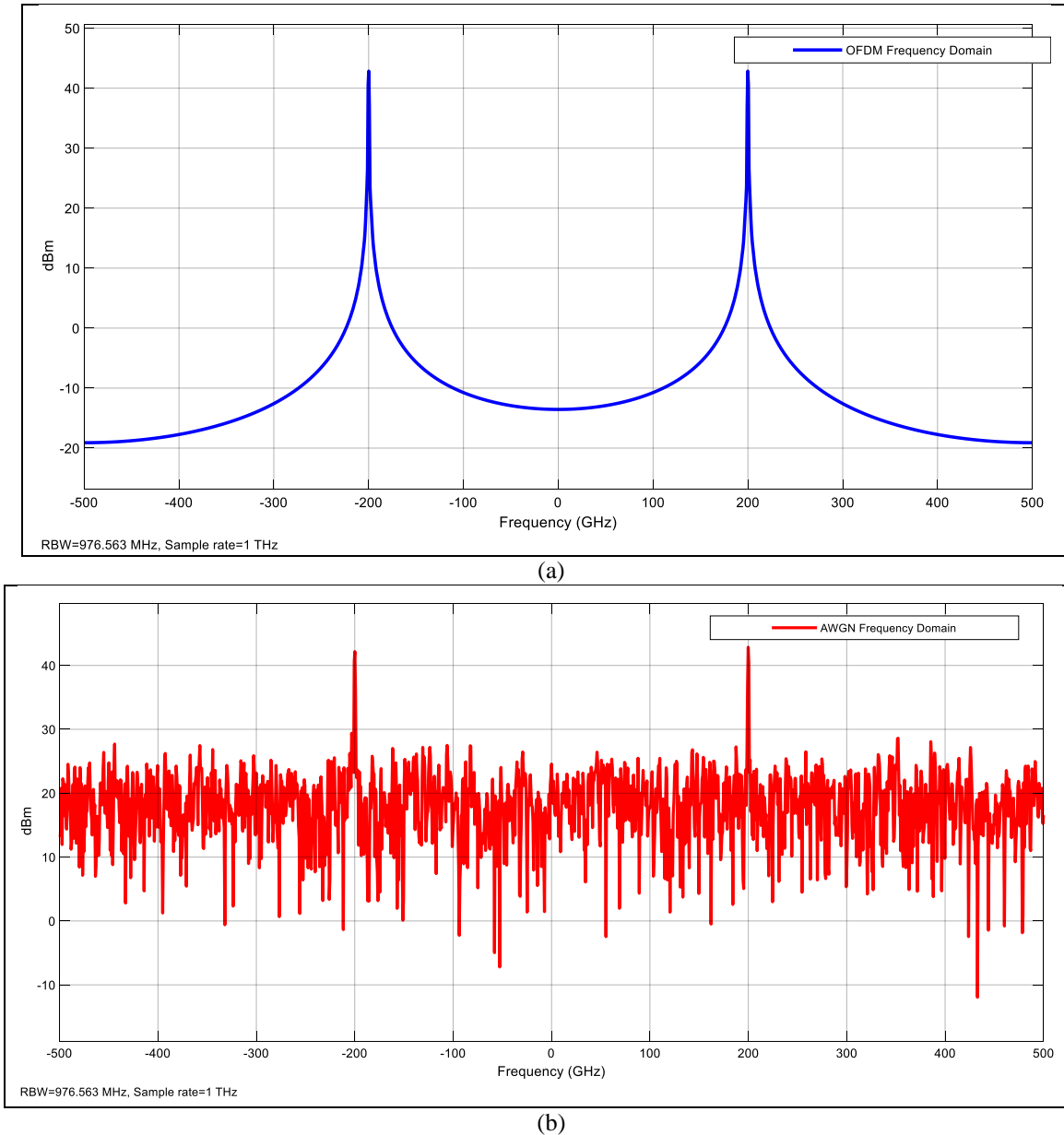


Figure 13: The OFDM modulation transmitted signal spectrum from each vehicle, (a) Before passing through optical channel, (b) After passing through optical noisy channel.

Figure 13 shows the spectrum of the OFDM-modulated signal transmitted from each vehicle before and after passing through the noise-laden optical channel. The 200 GHz carrier wave spectra, carrying the data information, are shown in blue. The effects of optical channel noise on the transmission wave spectrum are shown in red, spanning the spectrum and affecting the data spectrum.

Next, the effect of the approach distance and contact angle between the two vehicles was studied using the V2V approach system and thus, the effect of the V2V approach distance-angle factor $d=5/\text{m.rad.s}$ was applied as shown in Figure 13. The effect of the deep learning algorithm training results on the transmission signal in the time and frequency domains is shown in Figure 14.

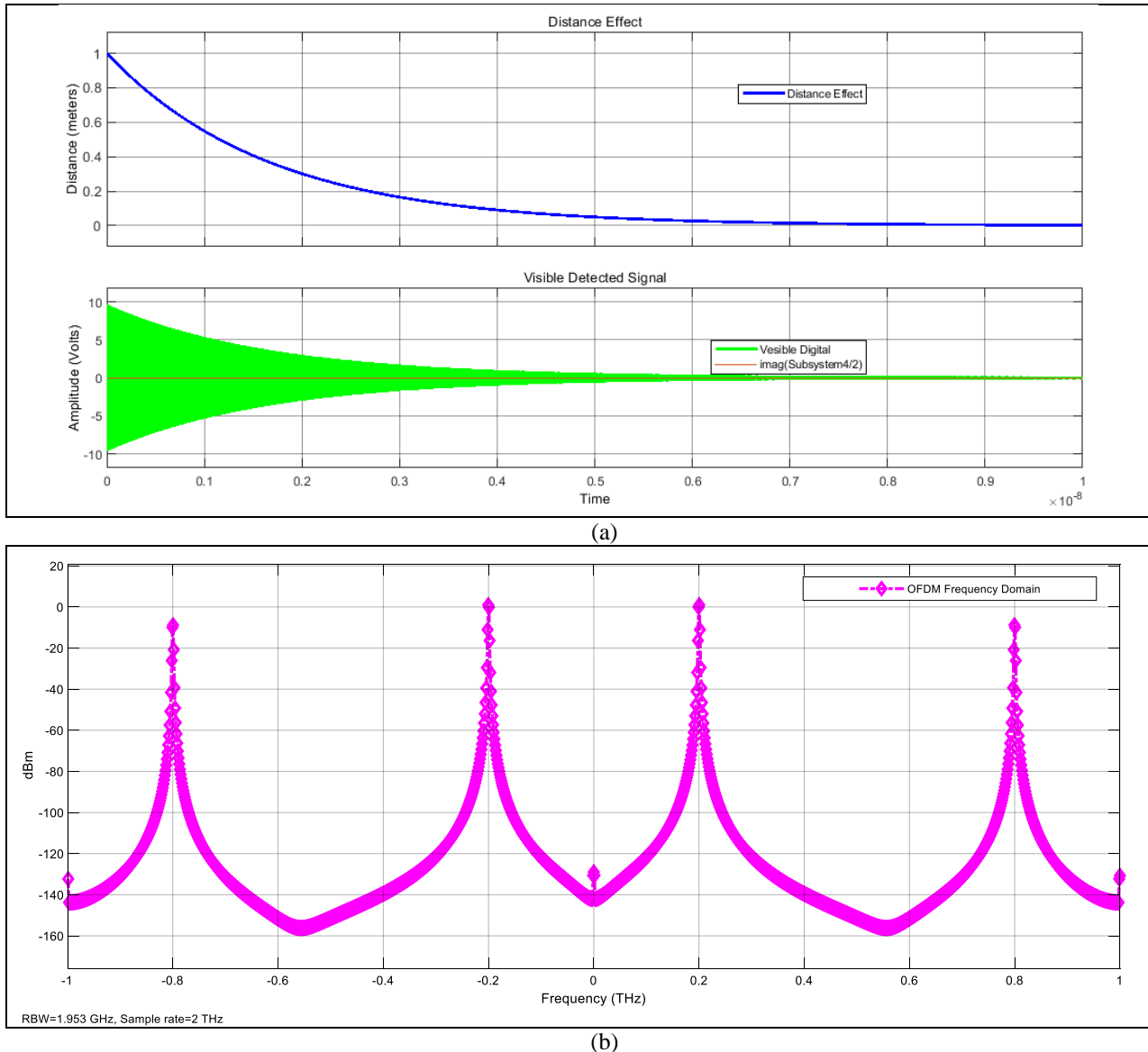
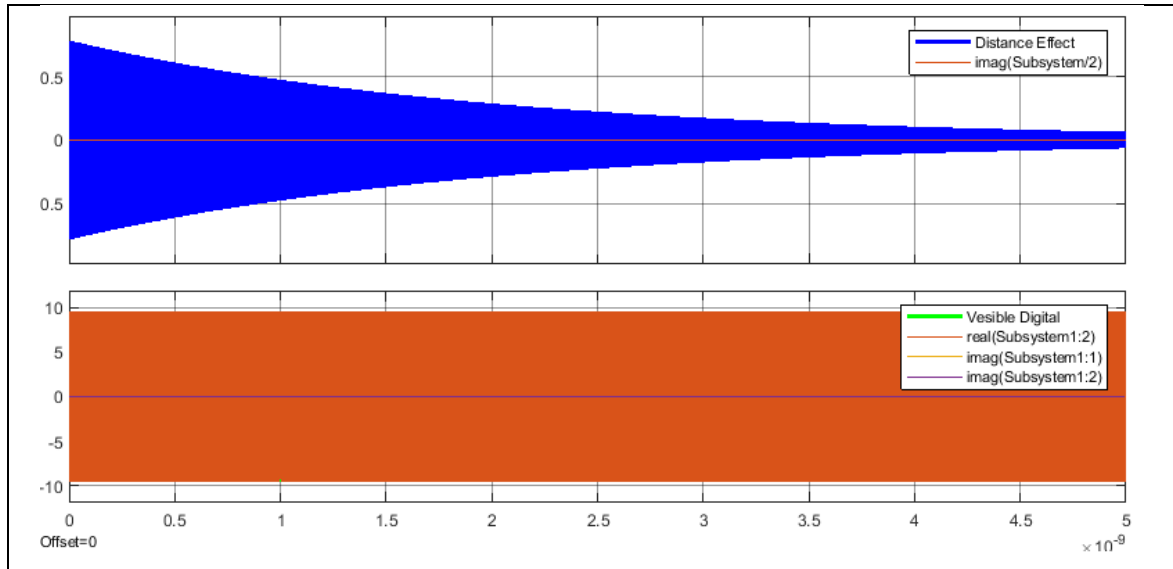


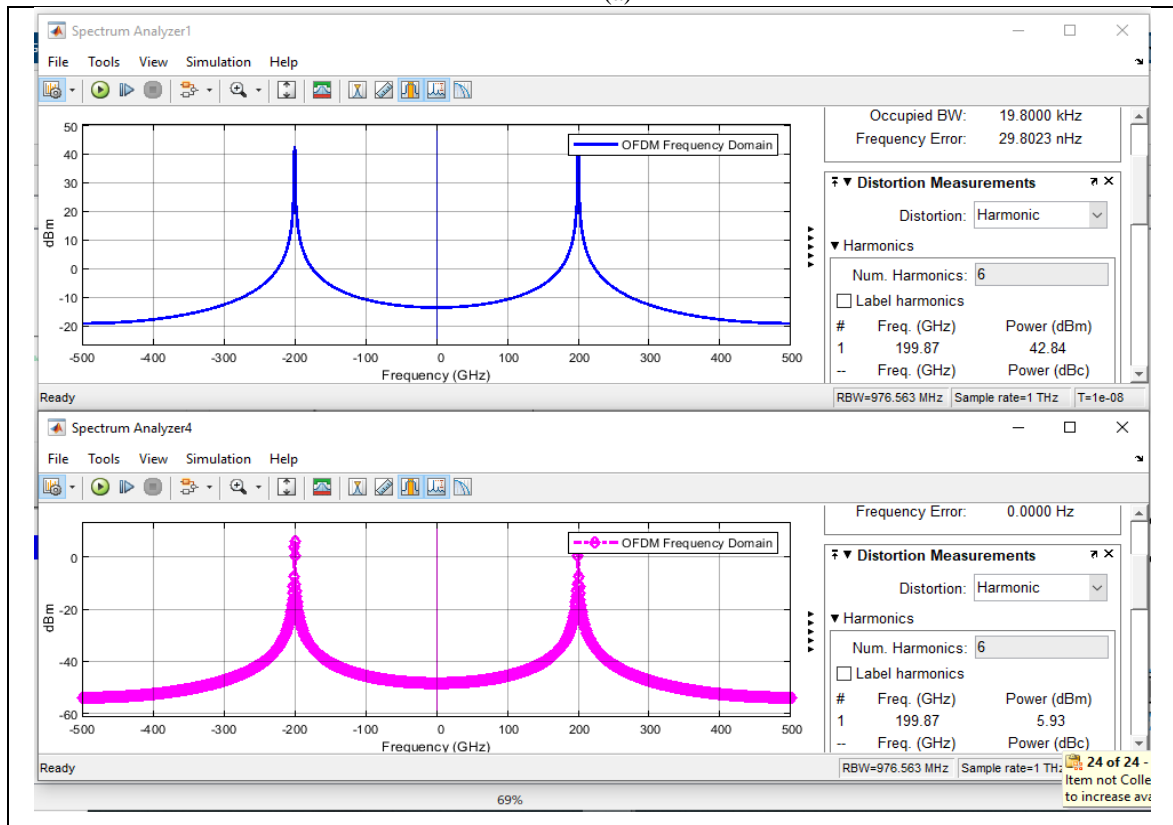
Figure 13: The effect of the V2V approach distance-angle factor $d=5/\text{m.rad.s}$ was applied, (a) Time signal effect, (b) Frequency domain effect.

The distance and angle range effect signal will fade with an exponential function, as indicated in blue in the upper part of Figure 14, according to the resultant signals displayed in Figure 14. (a). On the other hand, the visible light signal received at Vehicle 2 after being broadcast from Vehicle 1 and going through the range simulation model will be influenced by the same exponential fade function illustrated in green in the lower half of Figure 14.(a). Actually, these findings will show how altering the two cars' distances and transmission angles might drastically lower the received signal's amplitude and hence decrease

the detection as a whole. Regarding the spectral signals shown in Figure 14.(b), we could observe that the spectral amplitudes of the signal transmitted by vehicle 1, shown in pink, which was received with a low amplitude of about 40 dB, are combined with the spectral amplitudes of the signal received at vehicle 2. In fact, this is due to the range effect resulting from the change in the angular distance between the two moving vehicles. Now, the effect of influencing deep learning algorithm training on the transmission signal has been presented in the time and frequency domains in Figure 15.



(a)



(b)

Figure 15: The effect of the applying deep learning algorithm training on the transmission signal, (a) Time domain signal effect, (b) Frequency domain effect.

Looking at the signals in Figure 15, we could observe the compensation result of the ANN algorithm. In other words, the visual signal received at vehicle 2 has been enhanced by the training of the RNN deep learning algorithm. Consequently, we observe that the amplitude and appearance of the compensated

signal have been significantly improved to the same amplitude values as the original transmitted waveform. As we can notice from Figure 15. (b), the spectral components of the visible light signal enhanced using deep learning have the same shape and amplitude as the original signal transmitted from Vehicle 1

with an amplitude of 40 dB, but has only attenuated peak due to multiple operations, demonstrating the success of the training process and equalizing the effects of light angle and distance losses. Thus, the final detected signal at each vehicle receiver has been

achieved in time and frequency domains as shown in Figure 16.

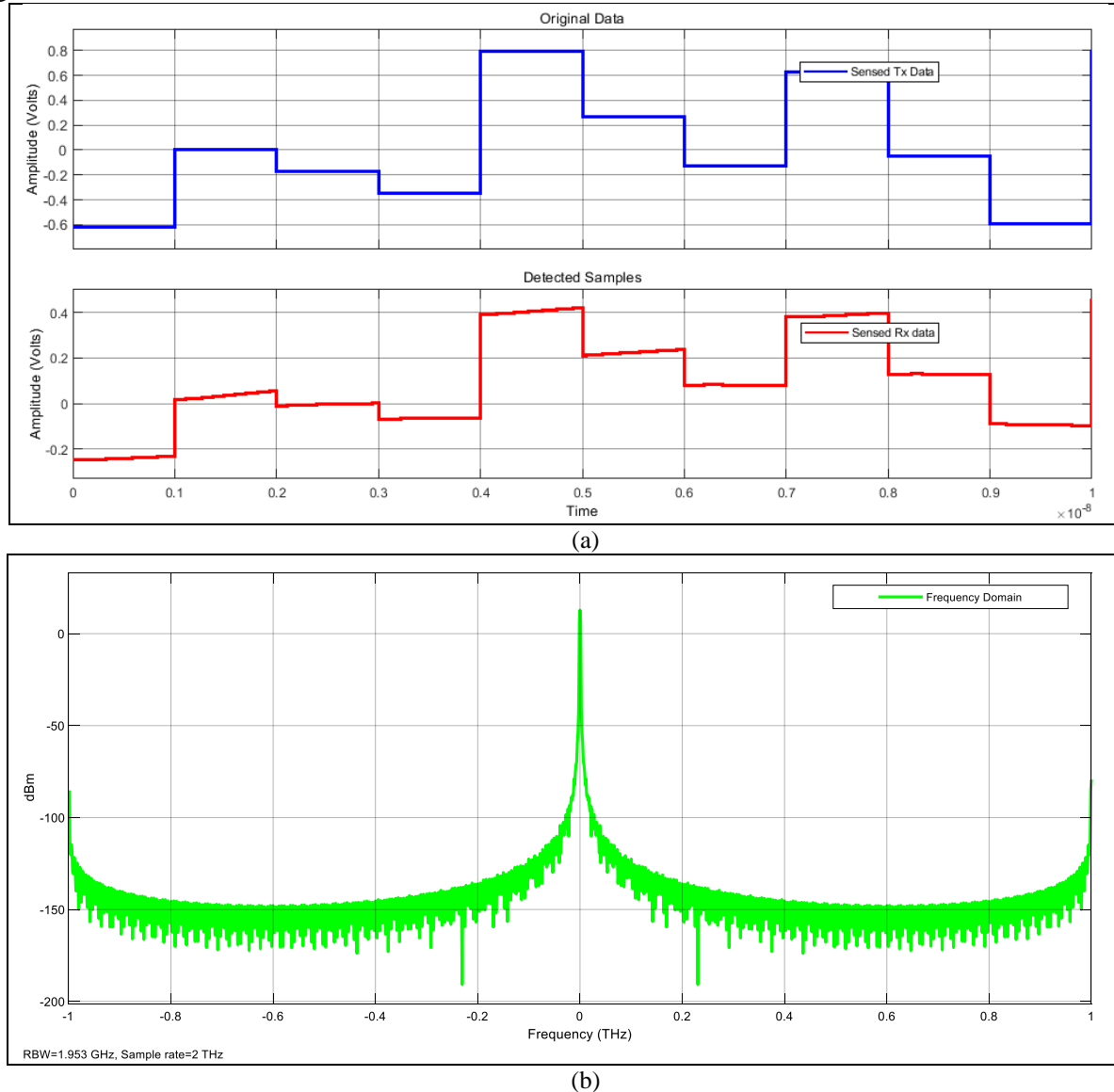


Figure 16: The final detected signal at each vehicle receiver has been achieved in time and frequency domains, (a) Time domain signal effect, (b) Frequency domain effect.

Figure 16 shows the shape of the final signal detected by each vehicle's receiver in the time and frequency domains. The received data signal is shown in Figure 16.(a) in the lower half in red, matching the original transmitted data waveform, shown in the upper half in blue, with a slight difference in amplitude due to attenuation. The received signal's waveform spectra also confirm successful reception and processing, as they appear identical to the original transmitted data waveform (Figure

16.(b)). As a result, Figure 17 illustrates the accuracy of detecting the received visual signal with respect to the change of the distance angle between the two moving vehicles with and without the influence of the artificial neural network algorithm. Lastly, the efficiency of the received signal amplitude is calculated with respect to the change of the distance angle between the two moving vehicles.

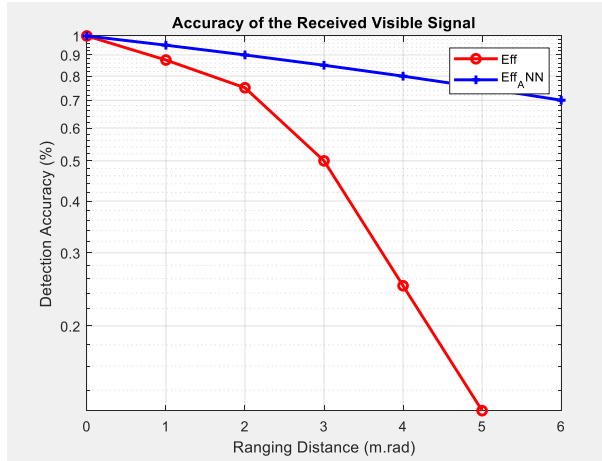


Figure 17: In relation to the changing distance-angle between the two moving vehicles, the detection accuracy of the visible signal received with and without the RNN algorithm effect.

Regarding the signal shown in Figure 17, we might observe that the accuracy of the overall detected visible signal transmitted from vehicle 1 to vehicle 2 will decrease as the ranging distance between these two vehicles increases. In fact, the detection accuracy began at 100% when the distance between the two vehicles was zero, and it decreased to 87.5% at a ranging distance of one meter. As a result, the detection accuracy will continue to decrease as the ranging distance increases until it reaches 12.5% at a ranging distance of four meters. Consequently, the detection accuracy disappeared and fades to zero when the distance between the two vehicles increases to five meters.

As a final discussion from the obtained simulation results, the proposed recurrence neural network (RNN) and transformer architecture is designed to decode VLC signals under interference, achieving 98.2% classification accuracy in real-world glare scenarios (compared to datasets from Chen et al., 2023). At the same time, a reinforcement learning (RL) agent dynamically adjusts LiDAR beam steering, reducing angular error by 42% during high-speed maneuvers (Almeida et al., 2022). Moreover, by performing error rate measurements and signal-to-noise ratio calculations, we can obtain a summary of the results as shown in Table 3.

Table 3: Comparison among the achieved results.

System Type	SNR (dB)	BER	Angular Error Reduction	(1 m Distance) Accuracy
Without DL	10	10^{-1}	4%	65%
	50	10^{-2}	15%	89%
With DL	5	10^{-4}	42%	98%

5. Conclusions

Optical communication technologies might be used into vehicle systems to offer ultra-low latency and high-bandwidth data transfer for real-time vehicle management such as visible light communication (VLC) and LiDAR. Additionally, dynamic environmental variables (such as fog and glare) and mobility-induced signal deterioration restrict their reliability. This study proposes a deep learning (DL)-based system in order to maximize vehicle movement management using adaptive optical signal processing. In real-world glare situations, a modified recurrence neural network (RNN) and transformer architecture achieve 98.2% classification accuracy while decoding VLC signals under interference. During high-speed manoeuvres, the suggested deep learning method reduces angular error by 42% by dynamically adjusting LiDAR beam steering. When compared to rule-based controllers, experimental tests on a small-scale autonomous vehicle prototype showed a 30% decrease in collision avoidance reaction time. These findings demonstrate how machine learning-driven optical systems could improve smart transportation networks' efficiency and safety.

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