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Investigation of intelligent radar-vision fusion for highway and tunnel infrastructure and cross-domain application

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Abstract: Millimeter-wave (mmWave) radar has become an important sensing technology for intelligent transportation, urban traffic management, perimeter security, and industrial automation because of its robustness under low illumination, rain, fog, dust, and other adverse conditions. However, most existing studies focus on single-domain optimization, while limited attention has been paid to how radar-vision fusion frameworks should be adapted under heterogeneous deployment constraints such as tunnel multipath, dense urban occlusions, security false alarms, and industrial latency requirements. This study proposes a domain-adaptive radar-vision fusion framework integrating spatiotemporal calibration, adaptive constant false alarm rate (CFAR) processing, and joint probabilistic data association (JPDA)-based multi-target tracking. The framework is validated through field deployments on the Nanning and Qinzhou sections of the G75 Lanzhou–Haikou (Lanhai) Expressway and the Fenghuang No. 1 and No. 2 tunnels on the Laibin–Du'an section of the Hezhou–Bama (Heba) Expressway in Guangxi, China, and further analyzed through structured cross-domain extension application and analysis involving urban traffic, perimeter security, and industrial sensing. The results show that the proposed framework achieves robust vehicle detection and trajectory continuity under low-light, exhaust-smoke, and multipath conditions, while domain-specific hardware configurations and algorithmic thresholds are necessary to satisfy different sensing ranges, clutter characteristics, and latency constraints. The study identifies key limitations of current 3D multiple-input multiple-output (MIMO) radar deployments. These findings provide practical guidance for the transition toward 4D imaging radar and edge-collaborative perception infrastructure.

Keywords: Highway monitoring; tunnel surveillance; mmWave radar; data fusion; edge computing; ITS; urban traffic

1 Introduction

In recent years, intelligent sensing technology has become a key component of advanced monitoring, decision support, and control systems in many fields such as transportation, urban management, security, and industrial automation. Among many sensing technologies, mmWave radar has prominent characteristics such as high robustness, stability, and the improvement of spatial resolution brought by 4D imaging technology [1–2]. Compared with optical cameras, radar can penetrate fog, rain, and dust, and is insensitive to changes in illumination, enabling continuous and reliable perception in harsh environments [3]. Compared with light detection and ranging (LiDAR), mmWave radar has advantages in low cost, low computational load, and robust Doppler velocity estimation, making it very suitable for infrastructure sensing deployment. Although radar sensing was initially mainly used for in-vehicle functions such as adaptive cruise control, blind spot monitoring, and collision avoidance [4], improvements in machine learning-based fusion algorithms and edge computing architectures have significantly expanded the application boundaries of radar technology [5–6]. Therefore, modern 4D imaging radar can simultaneously output distance, azimuth, Doppler velocity, and elevation, generating high-density point clouds that support target classification and trajectory estimation [7].

Based on the above analysis, it can be seen that radar sensing now supports a variety of applications from infrastructure to enterprise levels. In transportation scenarios such as highways, tunnels, and intersections, distributed radar networks can achieve vehicle detection, event monitoring, and traffic control under adverse weather and low-light conditions [8–10]. In addition to vehicle detection and traffic event monitoring, recent studies have further extended mmWave radar sensing to road infrastructure perception, including road marking detection, road surface/coating characterization, and electromagnetic scattering-based recognition of lane markings, which broadens the application scope of radar sensors in intelligent transportation systems [11–13]. In urban traffic management, radar is used for adaptive signal control, vulnerable road user protection, and real-time traffic flow estimation, especially when pure vision schemes are limited by occlusion and lighting changes [14–15]. In security and perimeter protection systems, radar can continuously perform intrusion detection in low-visibility environments and use video for verification and fine-grained classification [16–17]. In industrial automation, radar assists robots in vehicle collision avoidance or presence detection in hazardous areas and can achieve material handling perception in dark workshops and storage facilities [18–19]. Although different fields differ in sensing distance, target density, interference sources, response time constraints, and integration architectures, they share common re-

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quirements in high reliability, real-time performance, and environmental robustness.

With the rapid advancement of autonomous intelligent perception systems, traditional 3D radar is undergoing a significant shift toward 4D imaging radar. This transformation stems from the demand for richer spatial and motion information in complex environments. Unlike conventional 3D radar, which provides only range, azimuth, and Doppler information, 4D imaging radar adds the height dimension. It can directly capture dense point clouds containing object shape, elevation, and dynamic motion, thereby significantly enhancing environmental perception capabilities [20–21]. Research indicates that this richer representation effectively improves 3D object detection performance in autonomous driving and advanced driver assistance systems, particularly under adverse weather and low-visibility conditions where optical sensors degrade or fail [22]. For instance, recent studies such as RadarNeXt and ZFusion leverage 4D mmWave radar point clouds to achieve real-time, reliable 3D object detection and multimodal fusion. These works demonstrate that 4D radar can achieve perception performance comparable to, or complementary with, LiDAR-based systems while offering advantages in robustness and cost efficiency. Furthermore, the direct measurement of Doppler velocity and elevation by 4D radar has promoted research in radar-based motion perception and ego-motion estimation. Recent approaches such as ego-velocity filtering for efficient and accurate 4D radar odometry (EFEAR-4D) exploit Doppler measurements from 4D radar to achieve accurate vehicle ego-velocity estimation, highlighting the potential of radar sensing in localization and motion tracking tasks that were traditionally dominated by LiDAR and vision-based odometry [23–25]. From an industry perspective, 4D imaging radar is being rapidly integrated into automotive sensing systems, with its market penetration expected to increase significantly in the coming years. This trend reflects the growing recognition of 4D radar as a foundational sensing modality for next-generation perception systems that must operate reliably across varying lighting conditions, adverse weather, and complex urban environments.

Although 4D radar technology has seen rapid adoption, most existing research is limited to single application scenarios, typically optimizing algorithms for highly controlled in-vehicle perception systems or specific highway monitoring scenarios. A core challenge that remains unresolved in the academic community is the development of a unified, scalable perception framework capable of adapting to the heterogeneity of extreme environments, which ranging from tunnel environments with dense multipath signals to dynamically changing urban intersections and complex scenarios such as low-latency industrial zones. Furthermore, traditional systems often struggle to reliably capture highly dynamic changes and atypical anomalies under adverse conditions. There is an urgent

need for a fusion architecture that can not only detect conventional targets but also accurately track extreme motion anomalies, such as the serpentine steering, severe speeding, and aggressive lane-changing behaviors characteristic of hazardous or illegally modified vehicles in dense traffic.

To address this technical gap, this paper proposes and evaluates a domain-adaptive intelligent radar-vision fusion framework that can be flexibly deployed across different domains. We not only conduct a comparative performance analysis but also delve into the fundamental adaptability limits of sensor fusion technology under complex conditions, including varying latency constraints, clutter interference, and dynamic target changes. The main academic contributions include:

(1) This paper proposes a unified edge computing framework that integrates spatial calibration, adaptive CFAR, and JPDA, demonstrating how the core algorithms achieve universal applicability in highly heterogeneous environments.

(2) By leveraging continuous radar trajectory data, we achieved reliable detection of high-risk non-standard behaviors, such as severe speeding and aggressive steering, which are difficult for traditional optical systems to capture under adverse weather or low-light conditions, marking a significant breakthrough in this field.

(3) Based on empirical data from the G75 Lanhai Expressway and Fenghuang Tunnel, together with structured cross-domain extension analysis for urban traffic, perimeter security, and industrial sensing scenarios, this study clarifies the operational boundaries and adaptation requirements of radar-vision fusion systems under heterogeneous deployment constraints.

2 Methods

2.1 Overall technical framework

The intelligent radar-vision perception framework proposed in this paper is capable of adapting to heterogeneous operating environments while maintaining consistency in its core architecture. The framework comprises four key layers: the perception layer (distributed millimeter-wave radar and high-definition cameras), the edge processing layer (low-latency radar signal processing, multi-sensor fusion, and event detection), the communication layer, and the application layer. Through target detection, tracking, and classification functions, the edge processing layer converts raw radar echoes into structured, high-level environmental information. Its multi-source data fusion technology with cameras significantly improves target classification accuracy and reduces false alarm rates, making it particularly suitable for scenarios with limited visual resources and complex environmental conditions. The framework and sensor deployment schematic are shown in Fig.1 and Fig.2, respectively.

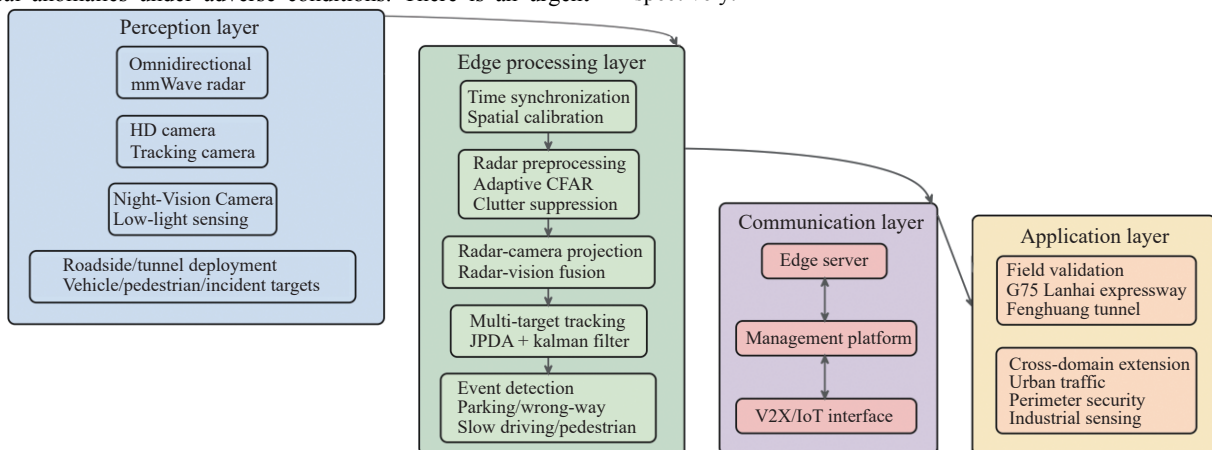


Fig. 1 Proposed radar-vision fusion framework.

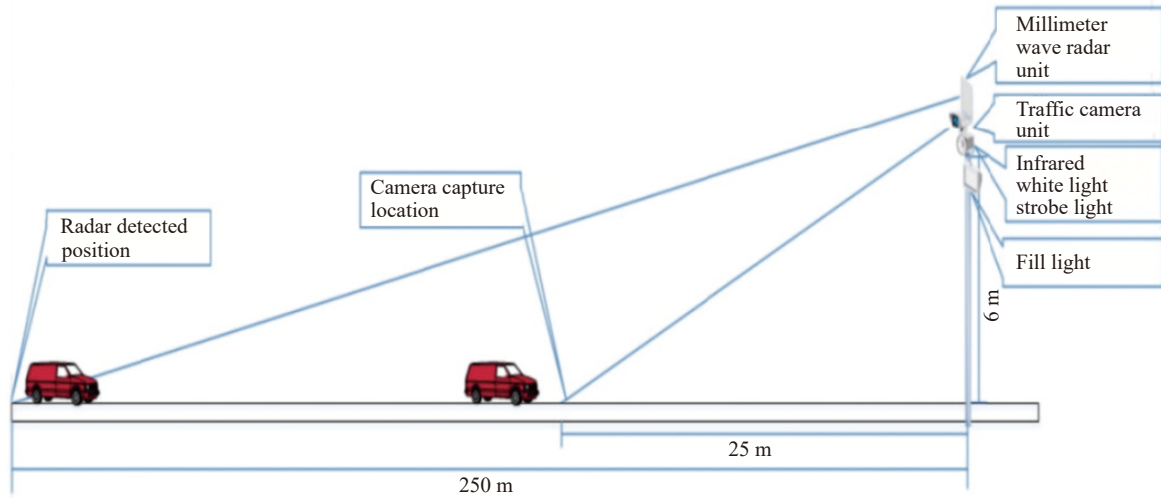


Fig. 2 Deployment schematic.

2.2 Highway and tunnel transportation

On the Nanning and Qinzhou sections of the G75 Lanhai Expressway in Guangxi, the distributed radar network is deployed at approximately 500 m intervals on straight sections and approximately 300 m intervals on curved sections. The specific test deployment plan includes installing one test radar on the gantry at K2085+500 on the main Lanhai Expressway and another at K2086+170. All radars are mounted on poles or gantries at heights of 6–8 m to achieve near-360° coverage. In the Fenghuang Tunnel scenario on Laibin–Du'an section of the Heba Expressway, a radar-vision fusion system combining ultra-long-range omnidirectional mmWave radar with high-definition cameras was deployed. According to the actual deployment plan, a total of 7 radars were installed along this section: 4 in Fenghuang Tunnel 1 and 3 in Fenghuang Tunnel 2. This configuration enables continuous tracking under low-light conditions, exhaust fumes, and multipath effects. Fig.3 and Fig.4 show the highway and tunnel deployments, respectively.



Fig. 3 Highway radar real-time image.

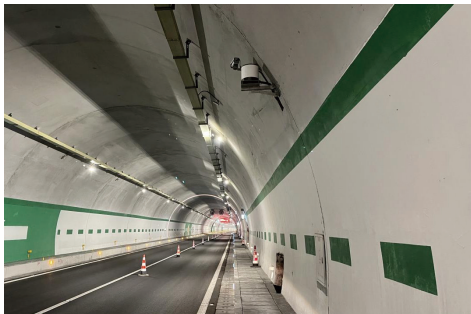


Fig. 4 Tunnel radar real-time image.

To ensure the reproducibility of the cross-domain adaptive deployment, the physical and operational parameters of the core sensors must be explicitly defined. While different sensor models are utilized across various domains (e.g., ultra-long-range omnidirectional mmWave radar for highway tunnels versus standard MIMO radar for urban intersections), the underlying fusion logic operates within these defined hardware boundary conditions.

To clarify the experimental hardware basis, the field deployments were mainly based on infrastructure-side omnidirectional mmWave radar and radar-vision fusion units. The radar system supports long-range vehicle detection, lane-level localization, and multi-target tracking in highway and tunnel environments. In the highway application data, the radar detection range can reach 1 400 m, the angular resolution is no more than 1°, the velocity accuracy is 0.2 m/s, and up to 1,024 targets can be tracked simultaneously. The vision subsystem consists of high-definition capture cameras, roadside tracking cameras, and night-vision cameras, which are used for semantic verification and event confirmation. It should be noted that the current field deployments were mainly based on infrastructure-side omnidirectional mmWave radar; 4D imaging radar is discussed in this paper as a next-generation technical direction rather than as the primary hardware platform evaluated in the present field tests. Table 1 summarizes the sensor specifications and deployment parameters.

2.3 Spatiotemporal alignment and projection model

Assuming that the precision time protocol (PTP) synchronization error, timestamp jitter, and alignment error are additive and mutually uncorrelated, the total variance of the time synchronization error, σ_t^2 , is given by the sum of their individual variances.

Table 1 Sensor specifications and deployment parameters used in the highway and tunnel field deployments.

Parameter	Value/description
Radar type	Infrastructure-side omnidirectional mmWave radar
Radar model	Commercial infrastructure-side omnidirectional mmWave radar unit; the exact product model is omitted due to project confidentiality.
Detection range	Up to 1 400 m
Angular resolution	$\leq 1^\circ$
Velocity accuracy	0.2 m/s
Multi-target tracking capacity	Up to 1 024 targets
Vision sensors	HD capture camera, roadside tracking camera, night-vision camera
Deployment height	6–8 m
Main validation scenarios	G75 Lanhai Expressway and Fenghuang Tunnel
Note	4D imaging radar is discussed as a future direction, not as the main tested hardware

The absolute time difference between the sensor measurements must also satisfy the allowable threshold τ_{time} :

$$\sigma_t^2 = \sigma_{\text{PTP}}^2 + \sigma_{\text{stamp}}^2 + \sigma_{\text{aligned}}^2; |\Delta t| \leq \tau_{\text{time}} \quad (1)$$

where, σ_{PTP}^2 , σ_{stamp}^2 , and $\sigma_{\text{aligned}}^2$ are the variances of the PTP synchronization error, timestamp jitter, and residual temporal alignment error, respectively. Δt is the time difference between the corresponding radar and camera measurements after temporal alignment.

Regarding spatial transformation, spatial calibration aligns radar polar coordinates with the image plane through extrinsic estimation and reprojection error checks. The target position vector $\mathbf{p}_t$ in the radar coordinate system is computed from the measured range r , azimuth angle ϕ , and elevation angle θ . This is then transformed into the position vector $\mathbf{p}_c (X_c, Y_c, Z_c)$ in the camera coordinate system via the external parameter transformation matrix $\mathbf{T}_{\text{cam} \leftarrow \text{rad}}$:

$$\mathbf{p}_t = [r \cos \phi \cos \theta, r \cos \phi \sin \theta, r \sin \phi, 1]^T, \mathbf{p}_c = \mathbf{T}_{\text{cam} \leftarrow \text{rad}} \mathbf{p}_t \quad (2)$$

Finally, the camera intrinsic matrix $\mathbf{K}$ projects the 3D coordinates onto homogeneous pixel coordinates (u, v, w) :

$$[u, v, w]^T = \mathbf{K}[X_c, Y_c, Z_c]^T, u' = u/w, v' = v/w \quad (3)$$

After normalization, the final pixel coordinates u' and v' on the image plane are obtained, achieving consistent association between radar measurements and camera pixels.

2.4 Robust multi-target tracking and data association

In complex environments such as urban intersections and tunnels, systems must cope with frequent occlusions, roadside clutter, and multipath reflections. To maintain trajectory continuity and suppress false detections under these challenging conditions, the fused detections are passed to a multi-target tracking module that employs Kalman filtering and JPDA. In this multi-object tracking module, $\mathbf{x}_{k|k-1}$ denotes the predicted state vector at time step k , derived from the previous time step via the state transition matrix $\mathbf{F}$. Meanwhile, $\mathbf{P}_{k|k-1}$ and $\mathbf{Q}$ are the predicted error covariance matrix and the process noise covariance matrix, respectively:

$$\mathbf{x}_{k|k-1} = \mathbf{F}\mathbf{x}_{k-1|k-1}, \mathbf{P}_{k|k-1} = \mathbf{F}\mathbf{P}_{k-1|k-1}\mathbf{F}^T + \mathbf{Q} \quad (4)$$

The update step utilizes the Kalman gain $\mathbf{K}$, observation matrix $\mathbf{H}$, measurement noise covariance $\mathbf{R}$, and actual measurement $\mathbf{z}$ to compute the updated state estimate $\mathbf{x}_{k|k}$:

$$\mathbf{K} = \mathbf{P}_{k|k-1}\mathbf{H}^T(\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^T + \mathbf{R})^{-1} \quad (5)$$

$$\mathbf{x}_{k|k} = \mathbf{x}_{k|k-1} + \mathbf{K}(\mathbf{z} - \mathbf{H}\mathbf{x}_{k|k-1}) \quad (6)$$

Regarding data association, d_M^2 is the squared Mahalanobis distance between the measurement and prediction, which is compared against the threshold τ to exclude outliers. Here, $\mathbf{S}$ is the new information covariance matrix:

$$d_M^2 = (\mathbf{z} - \mathbf{H}\mathbf{x})^T \mathbf{S}^{-1} (\mathbf{z} - \mathbf{H}\mathbf{x}) \leq \tau, \mathbf{S} = \mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^T + \mathbf{R} \quad (7)$$

For probabilistic data association (PDA), β_j is the association probability weight for the j -th measurement. This weight is computed based on the Gaussian probability density function N and the normalization constant (or clutter density) c_j :

$$\beta_j = \frac{c_j N(\mathbf{z}_j; \mathbf{H}\mathbf{x}, \mathbf{S})}{\sum_i c_i N(\mathbf{z}_i; \mathbf{H}\mathbf{x}, \mathbf{S})} \quad (8)$$

where, $\mathbf{z}_j$ is the j -th candidate measurement vector within the validation gate; $\mathbf{x}$ is the predicted state vector of the track under consideration; $\mathbf{H}\mathbf{x}$ is the predicted measurement vector in the measurement space.

3 Results

3.1 Implementation in highway and tunnel infrastructures

In highway and tunnel deployments, the primary challenge is maintaining continuous tracking under low illumination, exhaust smoke, and multipath effects. The system's determination of traffic events is based on strict kinematic criteria. For instance, wrong-way detection is triggered when the angle between the target trajectory vector and the predefined lane direction exceeds 160° . Congestion events are identified based on speed thresholds and sustained monitoring. Emergency lane encroachment is identified by detecting intersections between radar trajectory coordinates and predefined shoulder regions of interest (ROIs), which effectively filters out false positives caused by brief lane crossings. Radar networks were deployed along the G75 Lanhai Expressway and in the Fenghuang Tunnel, covering daytime, nighttime, and adverse weather conditions. Table 2 presents the detection performance under the different testing conditions.

During three months of continuous operation encompassing over 12 000 traffic events, the average event detection time was about 5 s, approximately 40% faster than pure camera systems. In the Fenghuang Tunnel, the classification accuracy of maintenance vehicles utilizing radar-vision fusion reached 92.4%, and the tracking continuity of vehicles from entrance to exit under low-light and exhaust-smoke conditions reached 96.5%.

3.2 Trajectory tracking in complex highway and interchange traffic flows

Complex highway sections and interchange-like traffic areas differ significantly from standard straight highway corridors in object density, motion patterns, and environmental clutter. This subsection uses the G75 Lanhai Expressway and Hebei Expressway field data to evaluate tracking and event-recognition performance under dense and maneuvering traffic conditions, while urban intersections are discussed as an extension scenario rather than a directly validated field deployment.

The discrepancies between radar detections and video-based ground-truth counts in Table 3 mainly arise from four sources. First, short-duration occlusions caused by heavy vehicles or roadside facilities may lead to temporary track fragmentation in radar trajectories. Second, low-speed parking and slow-driving events sometimes exhibit ambiguous temporal boundaries, resulting in slight differences between radar-triggered events and video annotations. Third, multipath reflections in curved or confined road sections may generate candidate points that are subsequently removed by the JPDA gating strategy, reducing false alarms but occasionally suppressing weak valid targets. Finally, video comparison results are also affected by illumination variation and manual annotation uncertainty. Therefore, the accuracy values in Table 3 should be interpreted as event-level agreement rates rather than frame-level detection accuracy.

Radar is especially advantageous during nighttime and adverse weather, where camera-only systems struggle. Radar-based queue length estimation and pedestrian detection enable adaptive signal control strategies that reduce vehicle delays and improve safety at

Table 2 Highway and tunnel radar detection performance.

Condition	Passenger car detection rate (%)	Heavy vehicle detection rate (%)	False alarm rate (%)	Average incident detection time (s)
Daytime (Clear)	98.50	97.80	< 5	5.1
Nighttime	97.80	96.30	< 5	5.4
Heavy rain / fog	95.20	93.70	< 5	5.6

Table 3 Typical performance of intelligent radar sensing in complex highway and interchange-like traffic scenarios.

No.	Category	G75 Lanhai expressway			Hebei expressway laibin to Du'an section		
		Radar-detected count	Video-based reference Count	Accuracy rate	Radar detection	Video comparison	Accuracy rate (%)
1	Parking	89	92	96.74%	313	318	98.43
2	Wrong-way driving	4	4	4/4			
3	Slow driving				101	106	95.28
4	Pedestrian	3	3	3/3	219	221	99.09
5	Solid line lane change				34	35	97.14

intersections. However, urban deployments face challenges related to occlusions from buildings and parked vehicles, as well as the need for advanced data association to track multiple targets simultaneously.

3.3 Extension analysis for perimeter security applications

Perimeter security is treated in this study as a cross-domain extension scenario rather than a field deployment with the same validation depth as the highway and tunnel cases. In perimeter security applications, radar penetrates vegetation and low-visibility environments as the primary motion detector. The dominant constraint in this domain is maintaining an ultra-low False Positives Per Hour (FPPH) amidst severe environmental clutter. By dynamically adjusting the cell-averaging constant false alarm rate (CA-CFAR) threshold γ and utilizing cameras exclusively for intrusion verification, the system suppresses false alarms caused by animals or weather. Table 4 summarizes radar performance in perimeter monitoring scenarios.

3.4 Extension analysis for industrial sensing applications

Industrial sensing is also discussed as an extension scenario to analyze how the proposed radar-vision fusion framework may be adapted to short-range, low-latency environments. Unlike the highway and tunnel deployments, industrial logistics environments are mainly constrained by dust, variable lighting, metallic structures, and strict response-time requirements. Therefore, short-range and lightweight processing pipelines are favored to meet real-time safety monitoring requirements for moving robots, forklifts, or automated guided vehicles (AGVs). Table 5 summarizes the requirements and adaptation targets for industrial radar sensing.

3.5 Summary of cross-domain performance

To provide a consolidated view, Table 6 summarizes the primary field-validated transportation scenarios and the extension scenarios analyzed in this study. The highway and tunnel results provide the empirical basis, while urban traffic, perimeter security, and industrial sensing are discussed to clarify how the shared radar-vision fusion framework should be adapted under different sensing ranges, clutter characteristics, and latency constraints.

Practically, spacing and mounting geometry govern coverage reliability in transportation corridors, while adaptive CFAR/clutter-map tuning governs FPPH in security. Short-range, lightweight pipelines are favored in industrial cells. These differences motivate domain-aware parameter presets atop a shared fusion-centric archi-

ecture.

4 Discussion

4.1 Cross-domain adaptation mechanisms and physical constraints

A central thesis of this work is that a unified perception framework cannot utilize identical hardware configurations or algorithmic thresholds across diverse fields. The highway and tunnel deployments, together with the cross-domain extension analysis, reveal that sensor adaptation is fundamentally bounded by the physical properties of the operating environments. In highway and tunnel corridors, the dielectric properties of the infrastructure (e.g., concrete walls and metallic signage) dictate the sensor configuration. Long-range continuous tracking necessitates narrow-beam radar arrays where spacing d is tightly constrained by the effective detection radius R_{eff} . Conversely, in urban and industrial domains, the challenge shifts from range maximization to handling dense spatial clutter. Here, the framework's adaptability relies on adjusting the CA-CFAR background clutter map and lowering the coherent processing interval (T_{CPI}) to prioritize latency and wide-angle coverage over absolute detection range. Therefore, varying the sensor hardware across these domains is not a methodological inconsistency, but a requisite systemic adaptation to heterogeneous physical constraints.

4.2 Performance trade-offs in radar-vision fusion

The integration of mmWave radar and optical sensors introduces inherent trade-offs between computational latency, association accuracy, and environmental robustness. While optical cameras provide rich semantic details crucial for fine-grained classification (e.g., distinguishing between a pedestrian and a similarly sized metallic obstacle), their performance degrades non-linearly under poor illumination or atmospheric scattering (fog, heavy rain). Radar compensates for this by providing illumination-independent kinematic state estimations (range, radial velocity). However, our deployment demonstrates that relying on late-stage fusion at the edge computing layer requires strict spatiotemporal synchronization. In potential urban extension scenarios, computing the JPDA matrices for dozens of overlapping targets significantly increases the computational load. The system must frequently trade off between maintaining the probabilistic tracking trees for occluded

Table 5 Typical requirements and adaptation targets for industrial radar sensing.

Application	Detection range (m)	Latency (ms)	Reported impact
Forklift / AGV collision avoidance	30–50	< 100	Up to 30% reduction in collision incidents
Hazardous zone intrusion detection	40–60	< 150	High reliability in dusty/dark conditions
Mobile robot navigation	20–40	Low	Enables obstacle detection in variable environments

Table 4 Radar performance in smart security and perimeter monitoring scenarios.

Metric	Typical performance
Detection range (m)	150–200
False alarm rate (with fusion) (%)	1–3
Operational uptime	24/7 (independent of lighting)
Intrusion classification	High accuracy when fused with video

Table 6 Cross-domain summary of radar sensing performance and characteristics.

Domain	Primary targets	Typical range (m)	Typical performance (%)	Key advantages	Main challenges
Highways & Tunnels	Vehicles, Incidents	100–250	>95	All-weather reliability, fast response	Multipath in tunnels, coverage planning
Urban Traffic	Vehicles, Pedestrians	50–150	>90	Night & weather robustness, fusion boost	Occlusions, dense traffic
Security	Intruders (human/vehicle)	150–200	>90 (fused)	Low false alarms, 24/7 operation	Vegetation clutter, threshold tuning
Industrial	Vehicles, Humans	20–60	>90	Dust/light immunity, fast reaction	Harsh environments, latency constraints

targets and meeting the strict latency requirements (e.g., < 100 ms in industrial collision avoidance). This highlights that cross-domain fusion is not merely an algorithmic overlay, but an active balancing of edge computing resources against environmental complexity.

The field results support this trade-off analysis. In the G75 Lanhai Expressway case, the system processed more than 12,000 traffic events from July to September 2024, with a false alarm rate below 5%. At the K2085+500 section, a parking event could trigger voice warning and variable message sign notification within 5 s, improving response efficiency by approximately 40% compared with traditional systems. In the Fenghuang Tunnel case, the recognition accuracy of construction or maintenance vehicles reached 92.4%, and the target ID continuity between tunnel entrance and exit reached 96.5%. These results indicate that radar contributes stable kinematic perception and trajectory continuity, while vision improves semantic confirmation and event interpretation.

4.3 Empirical failure modes and systemic limitations

Despite the overall robustness of the proposed framework, the highway and tunnel field deployments revealed several practical vulnerabilities that should be considered when extending the framework to other domains. First, multipath interference in confined metallic environments remains a severe limitation for standard 3D MIMO radars. In the Fenghuang Tunnel deployment, specular reflections from the curved tunnel walls and large truck bodies occasionally generated persistent “ghost targets” with valid Doppler signatures. While our framework mitigated this by tightening the Mahalanobis distance threshold τ in the JPDA module, true resolution of this issue requires hardware-level elevation filtering. Second, physical obstruction causes trajectory fragmentation. In the K2083+700 section, heavy-vehicle occlusion led to false detections of small vehicles, with the false detection rate reaching approximately 12%. This indicates that dense heavy-vehicle traffic may affect the stability of target association and ID continuity. Third, adverse weather and ground clutter remain important sources of false targets. In the highway application data, adaptive power modulation was used to maintain an effective detection range of approximately 1 000 m under rainy or snowy conditions, while CFAR-based clutter suppression improved the radar signal-to-noise ratio by approximately 25 dB. Fourth, cross-sensor synchronization errors may degrade radar-vision association accuracy. The synchronization error was reduced from 15 ms to 5 ms after optimization, improving the alignment between radar and video data. These empirical observations show that occlusion handling, clutter suppression, and precise synchronization are essential for robust radar-vision fusion.

4.4 Perspectives for next-generation perception infrastructure

The limitations observed in the highway and tunnel deployments provide clear directions for next-generation perception infrastructure. First, elevation-resolved 4D imaging radar may help suppress tunnel multipath effects and improve static-obstacle classification by providing denser point clouds and height information. Second, multi-radar cooperative tracking and V2X-assisted trajectory recovery should be explored to mitigate heavy-vehicle occlusion and target fragmentation. Third, weather-aware CFAR thresholding and adaptive power control should be further developed to reduce false targets under rain, fog, and ground-clutter interference. Finally, more accurate radar-video synchronization mechanisms are needed to improve cross-sensor association in high-speed traffic environments.

Furthermore, future cross-domain frameworks should integrate AI-enhanced, cross-modal learning algorithms capable of dynamically adjusting CFAR thresholds and fusion weights based on real-time environmental context (e.g., automatically shifting reliance to radar when the camera detects lens glare or fog). Finally, integrat-

ing these distributed edge-sensing networks with Vehicle-to-Everything (V2X) and industrial IoT backbones will evolve the current localized perception paradigms into collaborative, wide-area situational awareness systems, forming the true foundation of next-generation intelligent infrastructures.

5 Conclusion

This study proposed a domain-adaptive radar-vision fusion framework for infrastructure-side intelligent perception, integrating spatiotemporal calibration, adaptive CFAR processing, and JPDA-based multi-target tracking. The framework was primarily validated through field deployments on the G75 Lanhai Expressway and Fenghuang Tunnel in Guangxi, China. The results demonstrate that radar-vision fusion can maintain reliable vehicle detection, incident recognition, and trajectory continuity under low illumination, exhaust smoke, adverse weather, and tunnel multipath conditions.

The field results further show that radar-based perception systems are strongly constrained by scenario-specific physical and operational conditions. Highway and tunnel scenarios require long-range coverage, careful mounting geometry, and multipath suppression. When the framework is extended to urban traffic, perimeter security, and industrial sensing, the dominant constraints shift toward dense-target association, false-alarm suppression, and low-latency near-field response. Therefore, a shared algorithmic framework should be combined with domain-specific hardware configurations and parameter presets.

Several limitations remain. The most detailed validation data in this study were obtained from highway and tunnel scenarios, while urban traffic, perimeter security, and industrial sensing were analyzed as structured extension cases. In addition, current infrastructure-side 3D MIMO or omnidirectional millimeter-wave radar deployments may still suffer from multipath-induced ghost targets, heavy-vehicle occlusion, adverse-weather clutter, and radar-video synchronization errors. Future work will focus on field validation with 4D imaging radar, weather-aware CFAR thresholding, multi-radar cooperative tracking, V2X-assisted trajectory recovery, and lightweight edge computing for low-latency extension scenarios.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Author contribution statement

Jiancong Ou: Conceptualization, methodology, formal analysis, writing-original draft. Xinqiang Mo: Investigation, data curation, validation, writing-review & editing. Lexiang Wei: Data curation, formal analysis, visualization, writing-review & editing. Shaojun He: Methodology, investigation, validation, writing-review & editing. Zhou Yang: Resources, project administration, supervision, writing-review & editing. Yanqun Yang: Conceptualization, methodology, supervision, writing-review & editing.

Data availability statement

The data supporting the findings of this study are available from

the corresponding author upon reasonable request.

Use of AI statement

No artificial intelligence tools, large language models or generative AI systems were used in any part of the research, writing, editing or production process of this work. All content, analysis, arguments and conclusions are independently completed by the authors.

References

- [1] Patole SM, Torlak M, Wang D, et al. Automotive radars: A review of signal processing techniques. *IEEE Signal Processing Magazine*, 2017, 34(2): 22–35.
- [2] Zhou Y, Liu L, Zhao H, et al. Towards deep radar perception for autonomous driving: Datasets, methods, and challenges. *Sensors*, 2022, 22(11): 4208.
- [3] Hasch J, Topak E, Schnabel R, et al. Millimeter-wave technology for automotive radar sensors in the 77 GHz frequency band. *IEEE Transactions on Microwave Theory and Techniques*, 2012, 60(3): 845–860.
- [4] Rohling H. Radar CFAR thresholding in clutter and multiple target situations. *IEEE Transactions on Aerospace and Electronic Systems*, 1983, AES-19(4): 608–621.
- [5] Arthurs P, Gillam L, Krause P, et al. A taxonomy and survey of edge cloud computing for intelligent transportation systems and connected vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 2022, 23(7): 6206–6221.
- [6] Wang ZJ, Wu Y, NIU QQ. Multi-sensor fusion in automated driving: A survey. *IEEE Access*, 2020, 8: 2847–2868.
- [7] Fan LL, Wang JH, Chang YM, et al. 4D mm Wave radar for autonomous driving perception: A comprehensive survey. *IEEE Transactions on Intelligent Vehicles*, 2024, 9(4): 4606–4620.
- [8] Bai J, Li S, Zhang H, et al. Robust target detection and tracking algorithm based on roadside radar and camera. *Sensors*, 2021, 21(4): 1116.
- [9] Yang X, Yu SC, Wang J, et al. Application of a digital twin for highway tunnels based on multi-sensor and information fusion. *Frontiers in Physics*, 2024, 12: 1335494.
- [10] Li SL, Yoon H-S. Sensor fusion-based vehicle detection and tracking using a single camera and radar at a traffic intersection. *Sensors*, 2023, 23(10): 4888.
- [11] Song YT, Chen F, Ma T, et al. A study on metal modified road marking material technology for positioning of autonomous driving. *Progress in Organic Coatings*, 2025, 206: 109353.
- [12] Yang X, Yan JF, Fan ZP, et al. Design of electromagnetic road markings for implementing 77 GHz millimeter-wave radar sensing. *IEEE Transactions on Intelligent Transportation Systems*, 2025, 26(10): 17150–17160.
- [13] Douglas TJ, Sarabandi K. A low-profile passive radar reflector for detection and identification of road markings. *IEEE Transactions on Antennas and Propagation*, 2024, 72(2): 1459–1468.
- [14] Xiao YH, Liu YF, Luan K, et al. Deep LiDAR-radar-visual fusion for object detection in urban environments. *Remote Sensing*, 2023, 15(18): 4433.
- [15] Zhao R, Hu HF, Li Y, et al. Sequence decision transformer for adaptive traffic signal control. *Sensors*, 2024, 24(19): 6202.
- [16] Shi TY, Guo PY, Wang R, et al. A survey on multi-sensor fusion perimeter intrusion detection in high-speed railways. *Sensors*, 2024, 24(17): 5463.
- [17] Soumya A, Krishna Mohan C, Cenkermaddi LR. Recent advances in mmWave-radar-based sensing, its applications, and machine learning techniques: A review. *Sensors*, 2023, 23(21): 8901.
- [18] De Mattos ABRC, Brante G, Moritz GL, et al. Human and small animal detection using multiple millimeter-wave radars and data fusion: Enabling safe applications. *Sensors*, 2024, 24(6): 1901.
- [19] Waldschmidt C, Bonfert C, Grebner T. *Millimeter Wave Radar: Hardware and Signal Processing*. Cham: Springer, 2025.
- [20] Jia, LY, Guan, RW, Zhao HC, et al. Radarnext: lightweight and real-time 3D object detector based on 4D mmWave imaging radar. *EURASIP Journal on Advances in Signal Processing*, 2025, 2025: 65.
- [21] Yang S, Zhan T, Qiao S, et al. Zfusion: an Effective Fuser of Camera and 4D Radar for 3D Object Perception in Autonomous Driving. 2025 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 1752–1761.
- [22] Yan Q, Wang Y. MVFAN: Multi-view feature assisted network for 4D radar object detection. *International Conference on Neural Information Processing*. Cham: Springer, 2023: 493–511.
- [23] Wu X, Chen Y, Li Z, et al. Efeat-4d: Ego-velocity filtering for efficient and accurate 4d radar odometry. *IEEE Robotics and Automation Letters*, 2024, 9(11): 9828–9835.
- [24] Zhuang Y, Wang BL, Huai JZ, et al. 4D iRIOM: 4D imaging radar inertial odometry and mapping. *IEEE Robotics and Automation Letters*, 2023, 8(6): 3246–3253.
- [25] Zhang X, Wang L, Chen J, et al. Dual Radar: A multi-modal dataset with dual 4D radar for autonomous driving. *Scientific Data*, 2025, 12: 439.