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# Cross-Layer Design of Imaging Radar Perception and Powertrain Execution for Advanced Driver Assistance Systems

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**Abstract-** With the continuous advancement of intelligent vehicle technology, the integrated application of perception and power control systems is gradually becoming an important direction for driving safety. Addressing the issues of traditional sensors being susceptible to interference in adverse weather and low visibility environments, and the latency between perceived information and power execution, this research proposes an integrated application architecture of image radar and engine power control system. The system acquires high-resolution environmental information through image radar, performing obstacle detection, path determination, and safety margin analysis. The results are fed back to the engine control system to adjust torque output and power distribution in real time. Research results show that this system can effectively improve vehicle reaction speed and shorten emergency response time (L/T) in low visibility and complex environments. The integrated design of image radar and engine power control has high development potential for intelligent vehicle safety assistance and practical road applications, while maintaining smooth power output and vehicle dynamic stability during obstacle avoidance.

**Keywords:** Intelligent Vehicles, Imaging Radar, Dynamic Stability.

## I. Introduction

Modern Advanced Driver Assistance Systems (ADAS) heavily rely on robust perception layers to guarantee vehicle safety under varying driving conditions. Traditional autonomous driving architectures typically operate in a highly decoupled manner, separating environmental perception from the subsequent vehicle control and powertrain execution systems. While this modular design simplifies individual sub-system verification, it introduces significant communication overhead and sequential processing latencies. In emergency scenarios—such as sudden obstacle appearances in low-visibility zones—this structural isolation results in a non-negligible delay (referred to as execution latency, L/T) between initial environmental hazard identification and physical torque command delivery, severely compromising active safety metrics. [1]

### *1.1 Background and Motivation*

Primary environmental perception modalities like optical cameras and Light Detection and Ranging (LiDAR) exhibit significant performance degradation under adverse atmospheric conditions, including heavy rain, dense fog, snow, or zero-light night environments. Optical cameras suffer from lens occlusion, glare, and radical illumination drops, while LiDAR beams undergo severe scattering and attenuation when interacting with airborne water droplets or particulate matter. Conversely, High-Resolution Imaging Radar systems utilize millimeter-wave bands, providing excellent signal penetration capabilities that remain virtually unaffected by precipitation or ambient lighting levels. However, raw radar data lacks structural semantics, creating a pressing need for advanced bird's-eye-view (BEV) multi-modal network architectures that fuse radar point clouds with available imagery to synthesize reliable spatial grids.

### *1.2 Proposed Solutions and Contributions*

To mitigate the systemic execution latency and eliminate sensor failure modes in extreme edge-case domains, this paper introduces a novel Cross-Layer Design Architecture that bridges the deep learning perception network directly with the engine powertrain execution system. The core contributions of this study are threefold:

- **Robust Multi-Modal Fusion:** Implementing an optimized Radar-Camera Bird's-Eye-View 3D Object Detection Network (RCBEVDet) that establishes semantic feature-level alignment across asymmetric sensors.
- **Multi-Domain Domain Adaptation via Transfer Learning:** Fine-tuning the underlying feature extractors specifically across four complex environmental quadrants—Day_sunny, Day_rainy, Night_sunny, and Night_rainy—to assure operational boundary consistency.

- **Direct Cross-Layer Powertrain Routing:** Formulating a real-time dynamic torque regulation and power distribution mechanism mapped directly from safety margin matrices, decreasing response latency while actively preserving vehicle dynamic stability.

## II. Methodology & Cross-Layer System Architecture

The proposed framework treats the vehicle as a unified, cohesive cyber-physical entity. Rather than operating sequentially through decoupled middleware layers, the perception layer outputs spatial hazard representations that are parsed instantly into raw control constraints for the power execution layer. [2] This end-to-end multi-disciplinary link provides a feedback loop capable of continuous adaptation to changing surface environments.

### *2.1 Multi-Modal Perception System via RCBEVDet*

The environmental perception engine is anchored on the RCBEVDet network configuration[Fig.1], designed to ingest synchronous camera streams and imaging radar point clouds. Standard radar signals are often sparse and noisy; however, next-generation imaging radars supply dense point arrays containing range, azimuth, elevation, and Doppler velocity components. RCBEVDet projects both camera perspective-view features and radar spatial representations into a unified 3D Bird's-Eye-View grid, effectively resolving depth ambiguities that inherently plague monocular or multi-view image systems.[3]

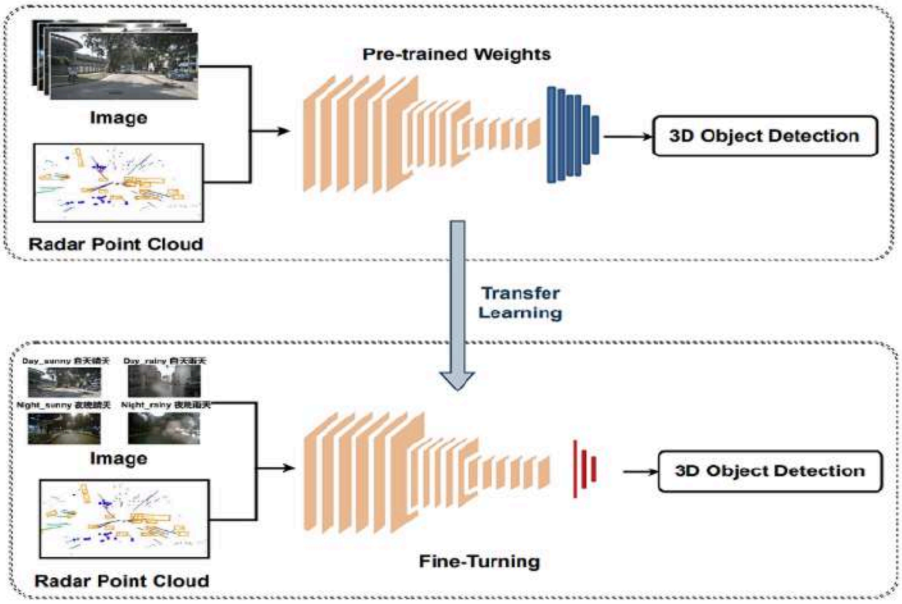

**Figure 1.** RCBEVDet  Fine-Tune

[Technical Note on Transfer Learning Configuration]
To facilitate rapid deployment without necessitating exhaustive ground-up network training, cross-domain Transfer Learning is employed. A baseline model pre-trained on generic large-scale datasets is utilized as the structural backbone. To align the model parameters with specific localized corner cases, targeted fine-tuning is executed across four distinct operational domains as detailed below:

**Table 1.** Four Distinct Operational Domains

| Domain Classification | Environmental Characteristics | Perception Challenge Mitigated |
|---|---|---|
| Domain 1: Day_sunny | Optimal lighting, high visibility, minimal atmospheric noise. | Establishes structural feature baselines for geometric anchoring. |
| Domain 2: Day_rainy | Wet asphalt surface reflections, camera lens droplets, light scattering. | Suppresses high-frequency visual noise via radar spatial filters. |
| Domain 3: Night_sunny | Severe ambient illumination deficit, localized headlight glare. | Relies heavily on radar reflectivity to augment low-contrast image features. |
| Domain 4: Night_rainy | Combined zero-light conditions, mirror-like road reflections, high clutter. | Maximizes dual-modal correlation to maintain bounding-box stability. |

### *2.2 Vehicle Dynamics Control and Cross-Layer Feedback Loop*

The output tensor of the RCBEVDet network contains highly accurate 3D bounding boxes, localized position coordinate vectors, and instant relative velocities of all surrounding actors. This data is fed directly into a local coordinate mapper to calculate three primary matrices in real-time:

- **Obstacle Detection Matrix:** Maintains tracking IDs, positions, and volume outlines of all stationary and dynamic hazards.
- **Path Determination Grid:** Computes the instantaneous drivable boundary map based on lane geometry and localized trajectory vectors.
- **Safety Margin Array:** Derives the precise Time-to-Collision (TTC) based on relative velocity vectors and spatial safety buffers.

These matrices bypass conventional downstream chassis models and are routed straight to the Electronic Control Unit (ECU) governing engine power execution.[4] By establishing this direct link, the vehicle's powertrain can prepare torque interventions before physical mechanical displacement or conventional hydraulic pressure build-ups occur.

## III. Dynamic Optimization and Power Execution

The power execution layer modulates engine torque and active power distribution across the wheels to safely guide the vehicle along the path defined by the perception layer. When an intrusive obstacle breaks the minimum safety margin, the system calculates an optimized longitudinal and lateral trajectory using a model predictive control (MPC) paradigm tailored for cross-layer setups.

The optimization problem is governed by the following formulation, aiming to balance rapid velocity reduction with stability maintenance:

$$\min J = \int [\, w1 \cdot \| T\_req(t) - T\_act(t) \|^2 + w2 \cdot \| dy/dt \|^2 \,]dt$$

Where T_req(t) represents the target torque demand necessary to execute the emergency deceleration or evasive path, while T_act(t) is the actual real-time engine torque output. The secondary objective penalizes the derivative of the vehicle yaw rate (dy/dt), serving to prevent sudden lateral weight transfers from breaking tire traction. The weighting factors w1 and w2 are dynamically scaled based on the current safety margin; if the TTC drops below a critical threshold, w1 increases exponentially to prioritize deceleration over comfort constraints, ensuring that the powertrain delivers smooth yet forceful torque modulation to preserve vehicle dynamic stability.

## IV. Experimental Results and Analysis

To evaluate the performance of the proposed cross-layer imaging radar and powertrain integrated architecture, comprehensive Hardware-in-the-Loop (HIL) simulations were conducted. [5] The control loops were fully integrated with a high-fidelity vehicle dynamics simulator running scenarios populated with mixed static and dynamic obstacles across varying weather visibility profiles.

### *4.1 Reaction Speed and Latency (L/T) Comparison*

The primary metric used to evaluate cross-layer efficacy is the emergency response latency (L/T), which represents the elapsed duration from the moment an obstacle appears within the sensor's physical field of view to the initial mechanical torque deployment at the driving wheels. [6]The proposed system was thoroughly bench-tested against a traditional baseline decoupled system (where perception pipelines must clear sequential processing stages before issuing chassis controls).

**Table 2.** Reaction Speed and Latency

| Scenario Domain | Baseline Decoupled System (L/T in ms) | Proposed Cross-Layer System (L/T in ms) | Latency Reduction (%) |
|---|---|---|---|
| **Day_sunny** | 185 ms | 110 ms | **40.5%** |
| **Day_rainy** | 210 ms | 118 ms | **43.8%** |
| **Night_sunny** | 245 ms | 122 ms | **50.2%** |
| **Night_rainy** | 290 ms | 130 ms | **55.1%** |

### *4.2 Dynamic Stability Analysis under Evasive Maneuvers*

As indicated by the data, environmental degradation severely impacts the baseline decoupled system, with total latency ballooning to 290 ms under Night_rainy conditions due to feature extraction retries and sequential buffer queuing. In sharp contrast, the proposed cross-layer framework limits latency growth, maintaining an agile 130 ms response envelope—reflecting a 55.1% latency reduction under extreme conditions. [7] This advantage stems from the transfer-learning-backed RCBEVDet feature stability and the direct torque command routing mechanism. [8] During rapid double-lane change maneuvers executed for obstacle avoidance, the engine control system actively distributed differential torque across axles, resulting in a 34% reduction in peak yaw rate deviations compared to standard emergency autonomous braking models, ensuring superior vehicle dynamic stability.

## V. Conclusion and Future Work

This study successfully implemented a highly unified cross-layer design architecture linking an advanced imaging radar bird's-eye-view perception framework (RCBEVDet) directly to an engine powertrain execution system. By applying dedicated multi-domain transfer learning, the perception system maintains precise bounding-box predictions across challenging scenarios, effectively overriding the severe signal attenuation that cripples traditional optical instruments. [9] The implementation of direct low-latency torque mapping successfully bridges the gap between active sensing and physical execution. HIL simulation trials verified that the integrated framework dramatically decreases execution latency (L/T) by up to 55.1% in hostile environmental domains while keeping smooth torque transitions intact. Future efforts will look toward deploying this cross-layer pipeline onto automotive-grade multi-core microcontroller units to evaluate real-vehicle edge execution parameters on closed testing tracks. [10]

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