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A Scoring Framework for Mode Selection Between High-Accuracy and High-Speed Fusion in Autonomous Driving

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Abstract. In autonomous driving, sensor fusion typically operates under two distinct modes. The high-accuracy fusion mode offers more precise environmental perception, but it requires substantial computational resources and introduces higher latency. In contrast, the high-speed fusion mode responds more quickly, albeit at the expense of some accuracy in specific situations. Balancing these two modes is a central challenge in designing perception fusion systems. Most existing studies focus on improving the fusion algorithms themselves, while relatively few explore a quantitative decision mechanism that selects between fusion modes based on driving scenarios. This paper proposes a mode-selection framework that enables dynamic switching between high-accuracy and high-speed fusion modes based on a multi-metric scoring scheme. The framework takes accuracy, stability, and latency as its core evaluation indicators. By applying normalization and weighted averaging, we establish a unified scoring metric that allows for flexible adjustment of weights according to real-world driving conditions. Using MATLAB simulations, we compare the two fusion modes under different scenarios and weighting configurations. The results show that the proposed scoring framework provides a quantitative and interpretable standard for balancing accuracy and speed, and it can automatically select the fusion mode with the higher score. This study offers a standardized and quantifiable decision-making approach for autonomous driving perception systems. It has the potential to enhance system safety while reducing unnecessary computational overhead.

Keywords: Sensor Fusion, Autonomous Driving, Fusion mode selection, Accuracy-Latency Trade-off, Performance Evaluation, Dynamic Decision-making.

1. Introduction

The stable operation of autonomous driving systems relies heavily on accurate 3D perception of the surrounding environment. Modern driverless platforms are typically equipped with multiple sensing modalities, including cameras, LiDAR, and millimeter-wave radar. This multi-sensor design compensates for the limitations of any single sensor, enabling a more comprehensive understanding of the environment. Sensor fusion plays a central role in this process by integrating the strengths of each sensor while mitigating their weaknesses, thereby improving the overall stability and reliability of the system [1]. However, fusion strategies must always navigate an inherent trade-off between accuracy and speed. High-accuracy fusion often requires extensive computation and feature

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extraction, resulting in slower processing and increased latency. In contrast, high-speed fusion provides a rapid response but may struggle to maintain sufficient accuracy in complex scenarios.

Most existing studies focus on improving the fusion algorithms themselves in an attempt to increase both accuracy and processing speed simultaneously [2]. In practice, though, no single fusion strategy delivers optimal performance across all real-world driving environments. Dense urban traffic, sparse highway conditions, nighttime driving, and adverse weather such as rain or fog all impose different requirements on system accuracy and latency [3]. Although the limitations of relying on a single fusion scheme are widely recognized, there is still a lack of a quantitative, standardized, and interpretable mechanism to guide fusion-mode selection across varying environmental conditions [4].

To address these challenges, this paper introduces a scoring framework based on multi-criteria evaluation. The framework quantitatively compares different fusion modes through three key metrics: accuracy, latency, and stability [5]. It allows weights to be flexibly adjusted according to real-world scenarios, providing a principled basis for switching between fusion strategies. MATLAB simulations are conducted to validate the feasibility of the scoring process under different scenario-dependent weight configurations.

2. Methodology

2.1. Overview of the system architecture

The proposed system is designed to enable dynamic switching between the high-accuracy and high-speed fusion modes in autonomous driving [6]. It consists of four core components: the sensor perception module, the environmental feature extraction and fusion module, the scenario-based quantitative scoring module, and the fusion-mode decision and switching module. These components work together to achieve an appropriate balance between accuracy and processing speed across varying driving conditions.

2.2. Sensor perception module

This module receives heterogeneous data from multiple sensors. For example, cameras provide 2D image information, LiDAR delivers dense point-cloud measurements, and millimeter-wave radar offers sparse point clouds enriched with velocity vectors. After complex synchronization and preprocessing, the data streams are passed to the fusion module.

2.3. Environmental feature extraction and fusion module

This module contains two general fusion pipelines: a high-accuracy mode and a high-speed mode. The high-accuracy mode performs deeper feature extraction and more intensive multi-sensor fusion, leading to higher precision but significantly increased computational cost. In contrast, the high-speed mode applies simplified feature extraction and shallow fusion, enabling lower latency but reduced accuracy. Within the proposed framework, both modes produce outputs such as detection scores, distance estimates, latency measurements, and computational load, which are then forwarded to the scoring module.

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2.4. Scenario-based quantitative scoring module

This study employs a unified scoring formula to evaluate fusion performance under different scenarios.

$$\mathbf{Score} = \mathbf{w_1 Accuracy} + \mathbf{w_2 Speed} + \mathbf{W_3 Stability} + \mathbf{w_4 SafetyPenalty}$$

The weights in the above formula correspond to accuracy, latency, detection stability, and penalties associated with missed detections or high uncertainty.

2.5. Fusion-mode decision and switching module

This module compares the scores generated by the two fusion pipelines. When the high-accuracy fusion mode achieves a higher score than the high-speed mode, the system selects the high-accuracy mode. Conversely, if the high-speed mode obtains a higher score, the system switches to the high-speed mode.

The system outputs the finally selected fusion mode under various strategies and driving scenarios, along with the corresponding normalized scores.

3. Result

3.1. Experimental setup

We implemented a multi-metric scoring framework in MATLAB to support decision-making between the high-accuracy and high-speed fusion modes. Each mode is evaluated under each scenario using four metrics: accuracy, latency, stability, and safety (derived from the miss-detection rate). All metrics are normalized within each scenario using min–max normalization. Latency and miss-detection rate are inverted after normalization to ensure that higher values consistently indicate better performance. Define linear weighted scores score= $\sum \mathbf{w_i f_i}$. The scoring function was validated using two baseline weight configurations—one prioritizing real-time performance and the other prioritizing accuracy—as well as a grid search over the weight space for sensitivity analysis. The results demonstrate that the scoring framework consistently yields mode selections that align with engineering intuition and remain interpretable across various weight settings and scenario conditions.

3.2. Scoring criteria and indicator definitions

We use a weighted scoring function:

$$\mathbf{score(s,m)} = \mathbf{W_{acc}} \bullet \mathbf{f_{acc}(s,m)} + \mathbf{W_{lat}} \bullet \mathbf{f_{lat}(s,m)} + \mathbf{W_{stab}} \bullet \mathbf{f_{stab}(s,m)} + \mathbf{W_{safety}} \bullet \mathbf{f_{safety}(s, m)}$$

where s represents the scene, the system includes Highway, Urban, and Rain Night modes. The 'm' denotes the mode, where mode1 indicates Highway Acc and mode2 indicates Highway Speed. f represents the normalized values of each metric, all mapped to the [0,1] range, where higher values

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indicate better performance. $\mathbf{f_{acc}}$ represents the precision. $\mathbf{f_{lat}}$ represents latency, $\mathbf{f_{lat}}$ = 1-norm(latency). This metric is inverted after normalization. $\mathbf{f_{stab}}$ represents stability. $\mathbf{f_{safety}}$ represents safety. It is constructed in reverse from the missed detection rate. $\mathbf{f_{safety}}$ = 1 - norm(miss_rate). The lower the rate of missed detection, the higher the safety score. The total weight satisfies $\sum \mathbf{w_i}$ =1, which is dynamically adjusted through policy selection or scenario changes.

3.3. Normalization method

To allow direct comparison of the relative performance between the two modes within the same scenario, each scenario is normalized independently using row-wise min–max normalization.

For a given scenario s and indicator vector x= $[\mathbf{x_{m1}}, \mathbf{x_{m2}}]$:

$$\tilde{\mathbf{x}}_{\mathbf{m}} = \frac{\mathbf{x_m} - \mathbf{min}(\mathbf{x})}{\mathbf{max}(\mathbf{x}) - \mathbf{min}(\mathbf{x}) + \boldsymbol{\varepsilon}}$$

If the indicator is minimized, use norm= $\frac{(\mathbf{x}-\mathbf{min})}{(\mathbf{max}-\mathbf{min})}$. Calculate the 1-norm again to maximize the metric value, and use Ɛ to prevent the denominator from becoming zero.

3.4. Simulation input

The simulated data in the script is shown in the table 1.

Table 1. Simulation data table of simulation input

	Accuracy	Latency	Stability	Miss-Rate
Highway	[0.96,0.88]	[110,60]	[0.82,0.86]	[0.02,0.05]
Urban	[0.93,0.86]	[130,55]	[0.78,0.88]	[0.05,0.09]
Rainway	[0.87,0.81]	[160,90]	[0.73,0.79]	[0.08,0.12]

Weight settings

Strategy A: Real-time first

$$\mathbf{w} = [\mathbf{w_{cc}}, \mathbf{w_{lat}}, \mathbf{w_{stab}}, \mathbf{w_{safety}}] = [0.30,0.45,0.15,0.10]$$

Strategy B: Accuracy First

$$\mathbf{w} = [\mathbf{w_{cc}}, \mathbf{w_{lat}}, \mathbf{w_{stab}}, \mathbf{w_{safety}}] = [0.50,0.20,0.20,0.10]$$

Rationale for Weight Selection:

Strategy A emphasizes latency, so the weight assigned to latency is increased accordingly. Strategy B prioritizes accuracy, and thus the weight for accuracy is elevated. The weight of the safety term is fixed at 0.10 to reflect that safety is essential but not the sole evaluation criterion.

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3.5. Experimental results

The following presents the data generated by the MATLAB simulation script.

Table 2. Data plot from simulation run

Scene	highway	Urban	RainNight	Avg
StrategyA:mode1	0.400	0.400	0.400	0.400
StrategyA:Mode2	0.600	0.600	0.600	0.600
StrategyA's Rec	Mode2	Mode2	Mode2	-
StrategyB:Mode1	0.600	0.600	0.600	0.600
StrategyB:Mode2	0.400	0.400	0.400	0.400
StrategyB's Rec	Mode1	Mode1	Mode1	-

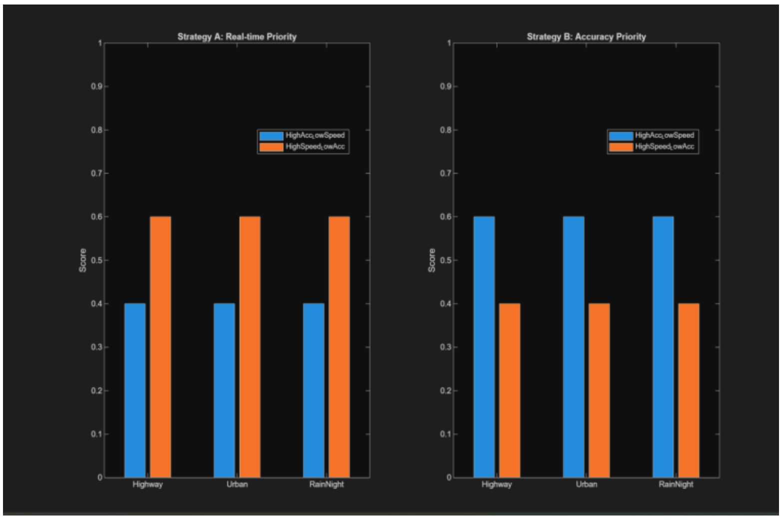

Figure 1. Data table from simulation run

3.6. Interpretation of results

In this study, the performance metrics of the two modes were normalized for each scenario. Taking the Highway scenario as an example, the two modes achieve extreme values in different metrics, resulting in normalized values close to 0 or 1. Specifically, for the accuracy metric, Mode 1 has a higher raw accuracy than Mode 2 (0.96 > 0.88). Therefore, the normalized accuracy value $\mathbf{f_{acc}}$ is 1 for Mode 1 and 0 for Mode 2. For the latency metric, Mode 2 exhibits a shorter response time, so its normalized latency value $\mathbf{f_{lat}}$ is set to 1, while Mode 1 is assigned 0. The stability metric $\mathbf{f_{stab}}$ also favors Mode 2, resulting in a normalized value of 1 for Mode 2. For safety, we use $\mathbf{f_{safety}} = 1 -$ norm(miss_rate) as the measure. Since Mode 1 has a lower miss-detection rate, its normalized f{safety} value is 1, while Mode 2 is 0.

Based on the above normalized values, the mode scores under Strategy A for this scenario can be computed as follows: Mode 1 achieves a combined score of 0.30×1 + 0.45×0 + 0.15×1 = 0.40,while Mode 2 scores 0.30×0 + 0.45×1 + 0.15×1 + 0.10×0 = 0.60. In contrast, under the accuracy-prioritized Strategy B in the same scenario, Mode 1 attains 0.50×1 + 0.20×0 + 0.20×0 + 0.10×1 = 0.60,whereas Mode 2 scores 0.50×0 + 0.20×1 + 0.20×1 + 0.10×0 = 0.40.

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Since the structural differences between modes are consistent across the three representative scenarios, the normalized components and weight combinations exhibit similar patterns. Therefore, in cross-scenario comparisons, the scores for Mode 1 and Mode 2 under the two strategies remain consistently at 0.4/0.6 and 0.6/0.4, respectively.

4. Discussion

The results above further demonstrate that when the weights for accuracy and safety-related penalties are high, the system tends to select the high-accuracy mode [7]. Conversely, when the speed weight is dominant and safety constraints are relatively loose, the system favors the high-speed mode. Regardless of how the modes switch, the scoring framework consistently produces clear and stable preferences, without abrupt oscillations or unreasonable decisions. These findings align well with expectations and confirm the inherent trade-off between accuracy and latency.

Although the scoring framework performs well in capturing overall trends, several sources of error and limitations remain. For example, the current simulations rely on simplified numerical models in which data distributions are overly idealized and the noise model is not sufficiently realistic. As a result, the framework may exhibit reduced stability in real-world scenarios. Moreover, a linear scoring formulation may not fully capture actual system behavior; weighted nonlinear functions and probabilistic models incorporating risk may be required.

This experiment addresses a gap in research on “mode-switching decision mechanisms.” The interpretable and extensible scoring framework proposed in this study helps fill this gap and provides a theoretical foundation for online decision-making in autonomous driving. Future work may incorporate real-world datasets for validation and integrate scenario recognition to enable more intelligent mode switching.

5. Conclusion

This study presents a quantitative scoring framework that dynamically selects between high-accuracy and high-speed fusion modes in autonomous driving perception systems. The results demonstrate that the proposed strategy is stable, consistent, and interpretable, showing that dynamic mode switching is controllable rather than unpredictable. While existing research primarily focuses on improving accuracy or reducing computational cost within a single fusion mode, few mechanisms have been developed to proactively switch fusion strategies in response to changing driving scenarios. To address this gap, this work establishes a weighted scoring model comprising accuracy, speed, and safety components, and integrates it into a decision-ready framework.

MATLAB-based simulations demonstrate that the proposed framework can automatically adjust its mode preference in response to changing weights. When accuracy is prioritized, the system consistently selects the high-accuracy fusion mode; when speed becomes the dominant factor, the framework switches to the high-speed mode.

Overall, the experimental results indicate that the dynamic scoring mechanism effectively balances perception accuracy and computational latency, enabling autonomous driving systems to adapt to different road conditions and perform real-time fusion-mode switching. This study provides a feasible path for dynamic optimization of perception modules and lays the groundwork for future extensions involving multi-sensor systems, diverse driving scenarios, and real-world environments.

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