FPT AI Residency Batch 6 Entry Test: Research Analysis Summary of Autonomous Vehicles' Collision-Avoidance Algorithms

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1 Scope & Motivation

Safe, reliable collision-avoidance (CA) is the last barrier between today's Advanced Driver-Assistance Systems and fully autonomous vehicles. The reviewed paper offers a panoramic scan of 300+ works (2020-2024) and groups them into four pillars:

Pillar	**Goal**	**Key Take-aways**	**Typical Gaps**
Sensor technologies	Turn raw world data into rich, timely perception	Cameras excel at semantics; radar at all-weather range; LiDAR at centimetre-level 3-D; fusion offsets single-sensor blind spots	Cost, weather artefacts, high data rates
Path-planning	Produce a feasible, safe, comfortable trajectory	Classical graph/sampling search is predictable; ML & heuristics adapt to dynamics; hybrids marry both	Computational load, local minima, sparse training data
Decision-making	Choose the manoeuvre (keep lane, overtake, stop. . .)	Rule-based logic is certifiable; probabilistic models quantify uncertainty; RL learns subtle interactions	Brittleness to edge cases, explainability
Machine-learning enhancers	Boost perception & prediction accuracy	Deep nets push SOTA in detection; DRL discovers human-like tactics; federated learning protects privacy	Big-data hunger, sim-to-real gap, "black-box" trust

Table 1: Summary of collision-avoidance pillars in autonomous driving.

2 Sensor Technologies in Collision Avoidance

Cameras recognise lanes, signs and vulnerable road users; with CNNs+YOLO reach real-time detection at 24 fps, yet degrade in glare or fog.

Radar penetrates rain/fog and gives precise Doppler speed; ML post-processing lifts position accuracy but needs heavy training sets.

LiDAR yields dense 3-D point clouds for centimetre-level mapping; costs and weather artefacts remain hurdles .

Sensor-fusion (camera+LiDAR+radar) outperforms solo sensors, yet demands complex time-synchronised pipelines and powerful on-board compute.

3 Collision-Avoidance Algorithms

3.1 Path-Planning

- Classical search – A*, Dijkstra, RRT/RRT*: deterministic, analyzable; enhanced variants (iADA*, THA*) re-plan on the fly for moving obstacles .
- Meta-heuristics – GA, PSO, ACO quickly explore huge search spaces but may stall in dynamic crowds.
- Learning-based – LSTM, CNN and self-supervised nets cut planning time by 25% in urban mazes; DRL (e.g., Neural-RRT*) adapts organically to unseen layouts.

3.2 Decision-Making

- Rule-based & fuzzy encode traffic law and expert heuristics, enabling certifiable baselines.
- Probabilistic (Markov/Bayesian) capture uncertainty in surrounding agents; Random-Forest lane-change predictors achieve >95% accuracy on NGSIM data.
- Reinforcement-Learning: hierarchical RL and soft-actor-critic planners outperform MPC in congested merging by learning cooperative cues.

4 Comparative Insights

- Deep learning lifts perception but needs terabyte-scale labelled data and struggles with explainability.
- Reinforcement learning masters multi-agent negotiation yet suffers long training cycles and risky exploration.
- Hybrid stacks (rule+ML) provide the best current trade-off: explicit safety envelopes hosting learning-based refinement.

Technique	**Specific Limitations**
Deep Learning (CNNs, RNNs, LSTMs)	Requires vast labeled datasets; computationally expensive; lacks interpretability ("black-box" nature); struggles with generalization in rare or extreme scenarios.
Reinforcement Learning (RL)	Long training times; challenges in sim-to-real transfer; potential risks in real-world exploration due to the exploration–exploitation trade-off.
Hybrid Approaches	Increased complexity in integration; potential latency in decision-making; requires extensive tuning and optimization for smooth performance.

Table 2: Specific limitations of advanced collision-avoidance techniques.

5 Real-World Evidence

Large-scale pilots validate lab gains but expose new challenges:

- Waymo: LiDAR-centric fusion reliably detects night obstacles; heavy rain still degrades returns.
- Tesla Autopilot: camera-only stack cuts sensor costs but has mis-detected parked trucks in low-contrast lighting.

- BaiduApollo: RL-augmented planner copes with dense Beijing traffic yet needs cloud-edge synergy for latency.
- A 2018 Uber fatality in Arizona reveals the high stakes of sensor fusion lapses and ambiguous pedestrian intent.

6 Research Gaps & Future Directions

- Edge-native ML – optimise networks for on-board inference under 10W power-budgets.
- Federated & privacy-preserving learning to crowd-source rare corner cases without sharing raw video.
- Sim-to-real transfer – domain randomisation + paired real-synthetic datasets to bridge the reality gap.
- Explainable AI & formal verification for regulators and public trust.
- All-weather sensing – photonic LiDAR, 4-D radar and event cameras to maintain perception in heavy snow or glare.

7 Bottom Line

Collision-avoidance for autonomous vehicles is maturing from single-sensor, rule-based pipelines to multi-sensor, hybrid-learning stacks. Robust CA now hinges on perception diversity, real-time compute, data-efficient learning, and ethics-aware decision-making. Continued cross-disciplinary research—melding AI, communications, embedded systems and human factors—will be key to achieving zero-collision mobility over the next decade.

References