Methods and Algorithms for Organizing Vehicle Autopilot System: A Review

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Introduction. The rapid advancement of vehicle autopilot technology is redefining the future of transportation systems, with a primary focus on enhancing road safety and efficiency by mitigating human-related factors. While existing Level 2 [1] vehicle autopilot systems have achieved partial automation in specific scenarios, higher-level systems (L3-L5) continue to encounter significant technical challenges: inadequate real-time performance and robustness in multi-sensor fusion, delayed collaborative decision-making in dynamic environments, and insufficient mechanisms for addressing complex ethical dilemmas. Current research has made strides in individual modules such as perception (e.g., LiDAR point cloud processing), planning (reinforcement learning and meta-heuristic algorithms), and control (MPC, fuzzy control)[2]. However, there remains a critical need for effective solutions in system integration and multi-agent coordination. Moreover, limitations in simulation testing and ambiguities in the ethical framework further impede the widespread application of this technology. We aim to optimize the organizational algorithms of vehicle autopilot systems, promoting the safe deployment and generalization capabilities of high-level vehicle autopilot through multi-module collaborative design, enhanced dynamic scene adaptability, and the construction of ethical decision models[3]. This work lays the theoretical foundation for the reliability and societal acceptance of intelligent transportation systems.

Main part. We provide an overview of the core technologies of vehicle autopilot systems, centering on the three modules of perception, planning and control:

1) Perception: Relying on multi-sensor (LiDAR, millimeter-wave radar, camera) fusion for environment sensing, emphasizing the importance of data denoising, feature extraction and fusion algorithms. Traditional methods rely on a priori knowledge, and deep learning methods (e.g., PointNet, VoxelNet) perform better in point cloud processing, but face real-time and hardware cost limitations[4]. Simulation test makes up for the lack of real scene data, but it still needs to be solved to improve the accuracy of complex light environment.
2) Planning and Decision Making: Traditional algorithms (A*, RRT) are effective in static environments but poorly adapted to dynamic scenes; machine learning and deep reinforcement learning optimize path planning through data-driven optimization but rely on a large amount of labeled data; and meta-heuristic algorithms (Genetic Algorithm, Particle Swarm Optimization) are suitable for complex constraints problems but are computationally inefficient[5]. One of the key issues to be addressed is the ethical decision-making mechanism (for example, emergency obstacle avoidance), which requires a combination of legal and ethical frameworks.
3) Control: Model Predictive Control (MPC) and fuzzy control can handle nonlinear

problems, but with high computational complexity; PID control is simple and easy to use, but with weak dynamic adaptability. Most notably, algorithmic accuracy needs to be balanced with real-time performance, and lightweight models need to be explored to reduce hardware dependency[6]. We will enhance the synergy between the various aspects, thus saving the time required to control the vehicle.

Conclusions. The current system suffers from insufficient subsystem integration, limitations of the simulation environment, and imperfect ethical decision-making mechanisms.

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