A Modular and Layered Perspective on Lateral Vehicle Motion Control: A Survey for ADAS and Autonomous Driving Systems

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Abstract— **This paper reviews modular and layered approaches to lateral vehicle motion control for Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) applications. Motivated by the growing need for scalable, reusable, and robust control architectures, the study systematically analyzes how existing academic and industrial contributions organize lateral control functionalities across four key domains: State and Parameter Estimation, Motion Limit Estimation, High-Level Control, and Low-Level Control. Special emphasis is placed on industry-backed implementations and emerging standardization efforts such as SAE J3131 and AUTOSAR. The review highlights practical advantages associated with functional decomposition, real-time constraint integration, and estimation-enabled control feasibility. By synthesizing insights from diverse sources, the work provides an architectural perspective that complements algorithmic advancements and supports scalable system integration for future ADAS and automated driving platforms.**

I. INTRODUCTION

Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) technologies have become key areas of research and development across academic and industrial sectors. Within the NCAP protocols, a broad range of ADAS functionalities are now systematically assessed and scored [1], while hands-free driving features continue to expand across the automotive market [2]. Meanwhile, significant progress has been made in autonomous applications such as robotaxis [3], hub-to-hub freight transport [4], and automation in confined environments like mining sites, yards, and logistics hubs [5], [6].

The SAE J3016 standard defines varying levels of driving automation, categorizing functionalities across Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD). These systems perform the Dynamic Driving Task (DDT), which consists of three key subtasks: Object and Event Detection and Response (OEDR), Lateral, and Longitudinal Vehicle Motion Control [7]. A critical distinction lies in the delegation of the OEDR subtask—handled exclusively by the human driver at Levels 1 and 2, and gradually assumed by the ADS from Level 3 onward, within a defined Operational Design Domain (ODD). In contrast, lateral and longitudinal motion control are increasingly automated even at lower levels, making them common ground between ADAS and AD architectures. This convergence suggests that motion control modules can be more readily standardized across systems, whereas the OEDR subtask remains the principal differentiator. Viewed through the Sense–Plan–Act framework, motion control corresponds to the Act phase, where shared design and implementation are more feasible.

Extensive research has addressed lateral vehicle motion control algorithms for both ADAS and AD. Amer et al. [8] provided a structured review, categorizing control strategies such as classical, geometric, optimal, adaptive, and predictive approaches. Stano et al. [9] focused on Model Predictive Control (MPC) techniques and their strengths in real-time path tracking. More recently, Artuñedo et al. [10] presented a harmonized benchmarking study comparing LQR, PID, Nonlinear MPC, and Model-Free Control under unified tuning and experimental conditions. While these surveys offer important insights into algorithm performance, they generally treat lateral control as a monolithic task, with limited attention to functional separation—such as trajectory tracking, actuator-level control, or constraint handling—or to modular or layered architectural organization across different automation levels.

In parallel, several industry-backed studies have proposed modular vehicle motion control (VMC) architectures supporting both ADAS and AD functionalities by decoupling trajectory planning from actuator-level execution. Tagesson et al. [11] merged driver-inferred and feature-generated inputs through a high-level controller. Klomp et al. [12] separated estimation, lateral, and longitudinal modules to enable trajectory planning independent of internal dynamics. Held et al. [13] and Münch et al. [14] proposed a layered structure, explicitly distinguishing the kinematic domain from dynamic control. Kron et al. [15] introduced fail-operational solutions for SAE Level 3 systems, and Li et al. [16] emphasized shared control and actuation layers across ADAS and AD. This modularity vision is formalized in standards such as SAE J3131 [17] and AUTOSAR [18].

Unlike algorithm-centric surveys by Amer et al. [8], Stano et al. [9], and Artuñedo et al. [10], which provide detailed analyses of controller structures, tuning methods, and performance outcomes, the aforementioned architecture-focused studies highlight how control responsibilities can be functionally separated, layered, and abstracted across reusable stacks. The modular and layered approaches proposed in these works align closely with emerging standards such as AUTOSAR [18] and SAE J3131 [17]. Yet, a systematic

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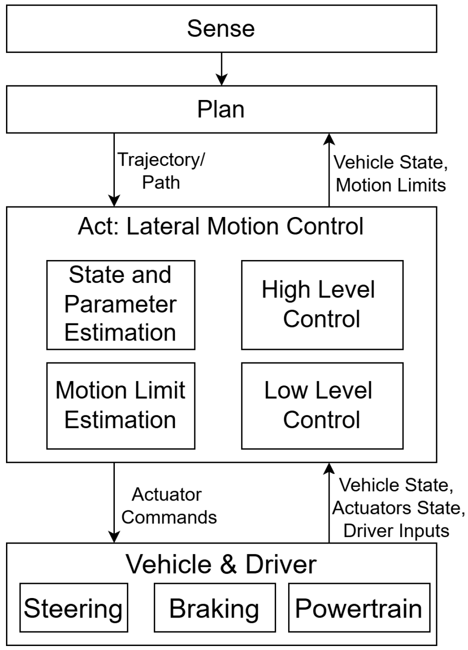

Fig. 1. Modular and layered lateral vehicle motion control architecture.

investigation into how lateral control algorithms map onto these structured architectures—particularly across different SAE automation levels—remains largely unexplored. Addressing this gap, the present study offers a functionally organized review of lateral vehicle motion control solutions across four key control blocks: State and Parameter Estimation, Motion Limit Estimation, High-Level Control, and Low-Level Control. Special emphasis is placed on studies co-authored by researchers from industry, ensuring that architectural applicability, deployment realities, and cross-domain scalability are adequately reflected.

II. MODULAR AND LAYERED LATERAL VEHICLE MOTION CONTROL ARCHITECTURE

Lateral motion control plays a pivotal role in the functional deployment of both Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) functionalities. As the level of driving automation increases, the complexity and performance requirements of lateral control systems also grow, necessitating scalable and adaptable architectural solutions. In this context, the adoption of modular and layered control architectures has gained increasing traction, particularly among industry practitioners seeking to support a diverse set of driving functions across varying SAE levels.

To conceptually organize this design space, we adopt the widely recognized Sense–Plan–Act paradigm, which partitions the perception, decision-making, and actuation responsibilities across the system. Within this framework, our focus lies on the “Act” phase, where lateral vehicle motion is realized through structured control modules. As illustrated in Figure 1, we propose a functionally layered architecture comprising four key components:

- **State and Parameter Estimation**, which reconstructs environmental and vehicular quantities such as sideslip angle, mass, road bank angle,tire-road friction, steering sensor offset necessary for control and motion limit estimation,
- **Motion Limit Estimation**, which determines operational boundaries for lateral dynamics (e.g., maximum curvature, yaw rate, and lateral acceleration) based on physical modeling and real-time estimation of states and parameters,
- **High-Level Control**, responsible for converting planned trajectories or paths into curvature or yaw rate references while considering motion limits,
- **Low-Level Control**, which translates those references into actuator-level commands (steering torque, steering angle), closing the control loop through execution.

These modules are designed to execute the trajectory provided by the motion planning layer. This architectural decomposition enables advantages such as reusability, independent development, and validation, and can be structured to support both ADAS and Autonomous Driving functionalities.

Importantly, this structure also enables domain separation, whereby ADAS and AD functions operate in a predominantly kinematic planning domain (handled by high level control), while low-level control operates in the dynamic domain. This distinction helps bridge the gap between feature-level behavior generation and real-time actuation, ensuring that planning decisions are mapped to executable and physically consistent trajectories.

In the following sections, we explore how this modular framework is instantiated in practice. Section 3 delves into representative implementations of High-Level and Low-Level Controllers, while Section 4 examines the enabling roles of State and Parameter Estimation and Motion Limit Estimation in supporting robust lateral control across varying SAE driving automation levels.

III. LAYERED LATERAL VEHICLE MOTION CONTROL

The architectural separation between high-level and low-level controllers is a core principle in modular lateral vehicle motion control design, particularly within scalable frameworks envisioned by standards such as AUTOSAR [18] and SAE J3131 [17]. In this context, high-level controllers (HLCs) are responsible for interpreting reference trajectories—typically defined in terms of path geometry or look-ahead targets—and converting them into curvature or yaw rate demands. These outputs serve as structured inputs for low-level controllers (LLCs), which generate corresponding steering commands based on actuator characteristics and vehicle dynamics.

This functional separation enables abstraction between planning and actuation layers, promotes component reuse across platforms, and provides robustness against vehicle parameter variations. Furthermore, it supports independent tuning and safety validation of HLC and LLC modules, which is especially important when targeting a range of SAE driving automation levels with different requirements for driver involvement and fallback behavior.

A. High Level Controllers

High-level lateral motion controllers are designed to translate reference paths or target points—generated by motion planning modules—into curvature or yaw rate demands that are feasible and dynamically consistent. Within modular architectures, the role of HLCs is to operate in the kinematic domain, decoupled from vehicle-specific dynamics and actuator behavior. This separation supports abstraction, ensuring that trajectory-following behavior can remain consistent even when underlying platforms differ in vehicle dimensions, steering configurations etc.

Across the reviewed literature, a variety of control strategies have been adopted in HLC design. A commonly implemented approach is Pure Pursuit, used for its geometric simplicity and robustness under moderate curvature tracking demands. It has been applied in the high-level control loops of several OEM and supplier studies, including those by Atoui et al.[19], Kapsalis et al. [20], [21], Kim et al. [22], and Rahman et al. [23], where the curvature demand is computed based on a look-ahead point along the reference trajectory. These studies often couple Pure Pursuit (PP) with low-level feedback control layers that compensate for unmodeled dynamics or actuator lag. In contrast, several studies have explored more advanced model-based high-level control strategies, particularly those utilizing Model Predictive Control (MPC) to derive curvature or yaw rate demands from planned paths under real-time constraints. Notable examples include the Lima et al. [24] and Pereira et al. [25], [26], contributions focused on autonomous truck control, which implement novel MPC formulations. Similarly, other works such as Weiskircher et al.[27] and Wang et al. [28] have adopted MPC-based high-level controllers that explicitly handle path-tracking constraints, dynamic feasibility, and curvature smoothness. These approaches demonstrate the ability of HLCs to combine kinematic planning outputs with predictive optimization, thereby increasing robustness and tracking accuracy—especially under fully autonomous driving conditions.

In addition to these model-based approaches, several studies employ combined feedback and feedforward structures in their high-level controllers to balance responsiveness and stability during path tracking. Notably, control frameworks proposed in earlier works from Rathgeber et al. [29], Ziegler et al. [30], and Keller et al. [31] incorporate yaw rate or curvature tracking feedback (FB) loops that blend reference feedforward (FF) components with lateral error feedback, sometimes complemented by disturbance rejection mechanisms. These architectures demonstrate how predictive compensation and error correction can coexist to support precise steering control in both assisted and autonomous modes. By contrast, the control strategy described in Awathe et al.'s recent studies [32], [33] bypasses conventional feedback altogether, using curvature outputs from the trajectory planner directly as control references—highlighting an architectural shortcut that may be viable for certain ADAS functions operating under tightly constrained conditions. Herstermeyer et al.'s LCA implementation [34], while not disclosing full algorithmic details, does indicate the use of a multi-loop structure that separates inner and outer control layers. While such structured layering remains less emphasized in algorithm-focused academic literature, these industrial implementations provide concrete evidence that layered high-level control designs are not only viable but actively applied in real-world systems—offering valuable architectural patterns that merit broader consideration.

B. Low Level Controllers

Low-level Controllers (LLCs) are tasked with converting curvature or yaw rate demands—typically generated by high-level controllers—into actuator-level steering commands that account for the vehicle's dynamic properties, actuator constraints, and environmental disturbances. Operating within the dynamic domain, LLCs directly interface with physical actuators and must handle nonlinearities, time delays, and uncertainties associated with vehicle behavior. Their primary role is to ensure that the control actions demanded at higher abstraction layers are executed in a stable, accurate, and physically realizable manner under real-world conditions.

Across the reviewed literature, low-level controllers predominantly employ feedback-based architectures grounded in measurable dynamic quantities such as yaw rate, steering angle, and vehicle velocity. These feedback loops are crucial for correcting deviations arising from unmodeled dynamics, parameter uncertainties, or environmental disturbances. In addition to conventional feedback design, several works—such as those from Walter et al. [35], Ziegler et al. [30], and Keller et al. [31] enhance low-level performance through feedforward augmentation, where anticipated system responses are preemptively compensated based on curvature or yaw rate demands. In contrast, Atoui et al.[19], Kapsalis et al. [20], [21] emphasize robust dynamic feedback strategies by employing Linear Parameter-Varying (LPV) frameworks, focusing on maintaining closed-loop stability across a range of operational conditions without relying on feedforward elements.

Furthermore, disturbance observer (DO) mechanisms have been integrated into low-level control loops in selected implementations, particularly by Walter et al. [35] and Kim et al. [22]. These observers estimate external disturbances such as crosswinds, road induced disturbances or steering actuator/sensor related errors, allowing corrective actions to be taken without relying solely on error feedback, thus improving tracking precision and robustness. Beyond dynamic tracking, several implementations explicitly address actuator constraints and driver interaction requirements. Studies from Walter et al. [35], Keller et al. [31], and Herstermeyer et al. [34] emphasize torque limiting, actuator saturation handling, and driver override detection to maintain safe coexistence between automated control and manual driver inputs, particularly in SAE Level 2 contexts. For example, torque outputs may be dynamically modulated based on driver-applied hand-wheel forces, allowing the system to prioritize human intervention when necessary, without destabilizing vehicle motion.

C. Summary of Algorithms for High Level and Low Level Controllers

To provide an organized overview of the reviewed studies, Table I categorizes the high-level and low-level controller designs.

TABLE I
LATERAL VEHICLE MOTION CONTROL ALGORITHMS FOR HIGH LEVEL AND LOW LEVEL CONTROLLERS ARCHITECTURE

Year	Ref.	HLC	LLC
2014	[30]	FB + FF	FF + DO
2014	[29]	FB + FF + DO	-
2014	[35]	-	FB + FF + DO
2015	[31]	FB + FF	FB + FF
2017	[24]	MPC	-
2018	[36]	-	FB + FF
2017	[27]	MPC	-
2019	[28]	MPC	-
2020	[25]	MPC	-
2020	[19]	PP	Robust LPV
2021	[20]	PP	Robust LPV
2022	[32]	Planner	FB + FF
2022	[21]	PP	Robust LPV
2022	[22]	PP	FB + FF + DO
2023	[33]	Planner	FB + FF
2023	[26]	MPC	-
2023	[23]	PP	FB + FF

As summarized in Table I, it is revealed that high-level and low-level controllers are consistently structured to reflect a kinematic–dynamic separation, with each layer targeting specific abstraction and execution roles. This decoupling facilitates platform-independent trajectory interpretation and actuator-aware execution, which is particularly valuable when designing systems for varying automation levels and vehicle configurations.

From a methodological standpoint, PP [20], [21], [22], [23] and MPC [24], [25], [26], [27], [28] dominate the high-level layer, yet their selection often reflects differing priorities: Pure Pursuit favors computational efficiency and ease of implementation, while MPC supports constraint handling and anticipatory behavior at the cost of higher computational demand. At the low-level layer, dynamic feedback controllers remain foundational. The integration of FB + FF combinations [35], [22], [37], [33] or DO mechanisms [35], [22] further enhances the adaptability of these controllers, especially against external disturbances and variations on vehicular and external conditions.

IV. MOTION LIMIT ESTIMATION AND STATE AND PARAMETER ESTIMATION

Effective lateral vehicle motion control relies not only on the precision of high-level and low-level controllers but also on the continuous and accurate estimation of the vehicle's internal states and motion limits. Addressing these needs systematically, two complementary estimation tasks are incorporated into the architecture: State and Parameter Estimation (SPE), which reconstructs critical dynamic variables and parameters in real time, and Motion Limit Estimation (MLE), which defines feasible motion envelopes to ensure operational safety and stability under varying conditions.

A. State and Parameter Estimation

State and Parameter Estimation encompasses multiple domains essential for robust lateral motion control. Real-time mass estimation, achieved through techniques such as Recursive Least Squares (RLS) and Extended Kalman Filters (EKF) [38], [39], enables controllers to account for dynamic payload variations, while enhancements for variable load conditions further improve predictive capabilities [40]. Estimation of inertial parameters like yaw moment of inertia and center of gravity height, has been addressed using observers operating on longitudinal and lateral dynamics [41], [42], [43], especially relevant for vehicles with unconventional mass distributions such as electric trucks. Sideslip angle estimation, crucial for lateral stabilization, has been reconstructed through Unscented Kalman Filters (UKF) [44] and lightweight kinematic observers [45] suitable for computationally efficient applications. Steering angle offset estimation has also been extensively explored, with methods for online calibration [46], [47] and adaptive marginalized particle filtering [48] ensuring consistent steering command interpretation without additional sensor hardware. The accurate estimation of the tire-road friction coefficient remains a critical challenge. Dynamic and vision-based fusion methods [49], [50] improve traction awareness, while recent studies have quantified the accuracy thresholds necessary for friction-adaptive control systems [51]. Finally, trailer state and parameter estimation plays a pivotal role in multi-unit configurations. Observer-based methods [52], [53] and radar-camera fusion techniques [54], [55] enhance trajectory tracking and stability for articulated combinations.

B. Motion Limit Estimation

Motion Limit Estimation dynamically defines the achievable operational boundaries of the vehicle, including maximum curvature, acceleration, and stability margins. By continuously assessing these limits under varying environmental and operational conditions, MLE ensures that motion planning and control actions remain feasible and safe.

AUTOSAR [18] introduces standardized interfaces for exposing vehicle motion constraints to upper-level planning modules such as realizable vehicle curvature - upper/lower limits, powertrain acceleration capability upper/lower limits. Modularized architectures, such as those proposed by Held and Heitmann [13] and Münch et al. [14], decouple motion limit estimation from specific actuator designs, promoting feature scalability and platform independence. For heavy-duty vehicles, where greater masses and dynamic variations are encountered, limit estimation frameworks must further adapt to payload changes and shifted centers of gravity, as highlighted by Tagesson [11]. Klomp et al. [12] emphasize that motion limits must integrate real-time friction, steering, and braking capabilities to enable safe degraded operations, such as minimum risk maneuvers, especially under adverse conditions.

C. Summary of State and Parameter Estimation Algorithms

State and Parameter Estimation (SPE) methods serve not only to reconstruct unmeasured vehicle states but also to enable modularity, adaptability, and robustness across control layers. Estimators provide virtual sensing capabilities that support High-Level Controllers (HLCs), Low-Level Controllers (LLCs), and Motion Limit Estimation (MLE) modules by abstracting dynamic behavior and hardware variability [14], [12], [18].

HLCs benefit from accurate knowledge of vehicle dimensions, tire-road friction, and trailer geometry to generate kino-dynamically feasible curvature and yaw rate requests. LLCs rely on real-time estimations of sideslip angle, steering offset, and inertial parameters to maintain stability and track demands under dynamic uncertainties. MLE modules use updated mass, friction, and configuration data to define safe operational envelopes, especially under degraded conditions.

Table II summarizes the mapping between estimation targets, their computational methods (e.g., Kalman filtering, observer design, perception fusion), and their architectural relevance. This overview emphasizes that estimator integration is not an ancillary feature but a foundational enabler of scalable and safety-aware motion control in both ADAS and Autonomous Driving (AD) systems.

TABLE II
STATE AND PARAMETER ESTIMATION ALGORITHMS AND THEIR ARCHITECTURAL RELEVANCE

Ref.	Est. Var.	Method	Arch. Rel.
[38]	Mass	RLS	LLC
[39]	Mass	EKF	LLC
[40]	Mass	Obs.	LLC
[41]	Inert. Par.	Obs.	LLC
[42]	Inert. Par.	Obs.	LLC
[43]	Inert. Par.	EKF	LLC
[44]	Sideslip	UKF	LLC
[45]	Sideslip	Obs.	LLC
[46]	SA Off.	RLS	LLC
[47]	SA Off.	Stat.	LLC
[48]	SA Off.	PF	LLC
[49]	Friction	Obs., RLS	HLC, LLC, MLE
[50]	Friction	Obs., Vis.	HLC, LLC, MLE
[52]	Trailer St.	KF	HLC
[53]	Trailer St.	Kinematic	HLC
[54]	Trailer St.	Perception	HLC
[55]	Trailer St.	Radar	HLC

V. CONCLUSIONS

This paper provides a structured review of modular and layered approaches to lateral vehicle motion control, emphasizing their relevance to Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) applications. Rather than proposing novel control strategies, the work synthesizes insights from industry-backed implementations, guided by standardization efforts such as SAE J3131 and AUTOSAR. Lateral control functionalities are categorized into four core domains—State and Parameter Estimation, Motion Limit Estimation, High-Level Control, and Low-Level Control—highlighting how functional decomposition enables scalable, platform-independent architectures. Across multiple studies, the consistent separation of high-level planning and low-level actuation layers fosters targeted validation, abstraction, and cross-domain reuse.

In low-level control design, the integration of feedforward and feedback paths, often supplemented with disturbance observers, enhances robustness under real-world uncertainties. State and parameter estimators—targeting friction, mass, inertia, and trailer articulation—play an essential role in enabling adaptive and disturbance-aware lateral control. Meanwhile, the increasing adoption of motion limit estimation, although less explicitly formalized in literature, reflects a growing recognition of the need to enforce real-time physical feasibility constraints. As a future research direction, investigating how modular and layered architectures can preserve safety when coupled with learning-based planners would offer valuable insight into bridging conventional control design with data-driven approaches.

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