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TOPICAL REVIEW

Comprehensive Control for Autonomous Vehicles: From Vehicle- to Human-Centric or From Integrated to Holistic?

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ABSTRACT The anticipated rise in the adoption of autonomous vehicles (AVs) has highlighted the need to redesign vehicle control architectures. This involves compromises guaranteeing performance and safety while addressing passenger comfort, which becomes increasingly critical as passengers shift from active drivers to passive occupants, making them vulnerable to motion sickness (MS). Despite the significant number of research studies examining MS mechanisms, quantification methods, and mitigation strategies, current control approaches seldom incorporate passenger states into the vehicle control loop. Nevertheless, a review of the literature reveals that existing definitions of a "holistic controller" are either vague or fragmented. Acknowledging the necessity to harmonize diverse methodologies and delineate a consolidated definition of a holistic framework, this review initiates with a thorough exposition of vehicle-related state estimation and control methodologies, accentuating the proposed literature solutions on holistic approaches. A critical distinction emerges between traditional integrated control, relying on separate, loosely-coupled modules with limited inter-module communication and vehicle-centric optimization, and the proposed holistic control featuring a multi-level architecture with bidirectional information flow, adaptive parameter weighting, and simultaneous consideration of vehicle and passenger subsystems to achieve multi-objective optimization encompassing safety, comfort, and overall efficiency. Additionally, a comprehensive discourse on the necessary additional module regarding the passenger state estimation techniques is presented, with a particular emphasis on those targeting head motion, which is closely associated with the onset of MS, with the following discussion focused on the sensing strategies employed in relation to the underlying vehicle estimation frameworks. In light of the aforementioned insights, the paper proposes the concept of a holistic controller, defined as a multi-level structure that collectively considers heterogeneous subsystems to achieve multi-objective optimization by managing trade-offs between competing objectives. Finally, the requirements and feasibility of such a framework in real-world applications are discussed, outlining how current research is evolving, defining the incoming demand for modular frameworks, high-performance computing, and shared solutions.

INDEX TERMS Autonomous vehicles, vehicle state estimation, motion control, holistic motion control, multi-objective optimization, motion sickness, passenger state estimation.

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I. INTRODUCTION

Over the past two decades, autonomous vehicles (AVs) have attracted growing interest from both academic researchers and industry leaders. Driven by rising safety standards, a demand for enhanced comfort and the automotive industry's shift toward higher levels of automation, AVs are increasingly seen as a cornerstone of future mobility.

To date, in the design phase of control systems, the focus has always been exclusively on the vehicle, with a varying level of detail, possibly pursuing other objectives such as tire wear [1], [2], [3], [4], [5], pollution emissions, or fuel economy optimization [6], [7], [8], [9].

Beyond traditional vehicle dynamics, modern architectures must accommodate interactions with external systems that fundamentally alter the optimization landscape [10]: vehicle-to-everything (V2X) communications introduce cooperative sensing and distributed computation possibilities [11]; energy efficiency requirements (particularly critical for electric vehicles) demand integration of powertrain optimization with vehicle dynamics control [6], [7]; environmental considerations (including long-term emission reduction and tire wear minimization) add additional objectives that must be balanced against traditional performance and safety metrics [4], [12]. Furthermore, the development of AVs is increasingly driven by a wide range of factors beyond technology alone. Indeed, as the human role transitions from active driver to passive occupant, comfort becomes a central design priority, alongside safety, efficiency, and user acceptance.

In this context, the inherent nature of AV contributes toward amplifying motion sickness (MS) phenomenon [13], [14] and emphasizing the need for more sophisticated vehicle control solutions [15]. Given the complex nature of motion sickness, the phenomenon has to be investigated considering both its mechanism and measurement as well as the multiplicity of methods for its mitigation. Prior studies [13], [16], [17], [18], [19], [20] have been developed around the idea of exploring these concepts. However, as the MS perceived by the occupants is directly connected to their motion in the cockpit [21], a detailed examination on how the passengers' states can be obtained needs to be considered. Moreover, the design of future vehicles should consider scenarios in which passengers are not oriented in the direction of travel (e.g. when seated in backwards facing seats), while engaged in non-driving-related tasks such as reading, working on a laptop, watching a movie or sleeping [22]. Therefore, the addition of MS mitigation in vehicle control modules, will force to redesign the overall structure, being based on a multi-level (both passenger/vehicle estimation and control) scheme.

Comprehensive or holistic solutions in the field of vehicle dynamics and control have often been proposed; however, those concepts do not fully reflect the latest needs and appear overblown as they can refer to a multiplicity of systems and solutions. This highlights the need for a clear vision aimed at achieving both comfort and performance in the design of future vehicles. Given the rising number of individual works, the theme of motion sickness mitigation has motivated researchers to develop structured reviews. The challenge becomes more pronounced when considering that modern autonomous vehicles must balance multiple competing objectives: minimizing sensor costs while maximizing information content, ensuring robustness while achieving precision, and maintaining computational efficiency within the constraints of embedded automotive ECUs [23], [24]. It should be underlined that as the number of variables increases the corresponding computational load and techniques complexity increases, therefore the designer should precisely choose the most representative yet minimal set of state variables for each application.

Saruchi et al. [17] defined the factors that can provoke motion sickness. They were listed as occupant- and vehicle-dynamics related: the first being related to sensory conflict theories, head tilting, subjective vertical conflict (SVC) and psychology; while the latter describing the effect of vehicle motion that can negatively interfere with passenger's comfort. The dissemination continued by analyzing the quantifying methods to evaluate the correct level of discomfort related to MS, including questionnaires, mathematical expressions/models and sensors, able to track passenger's state. Finally, the authors introduced the mitigation strategies from two different points of view: the vehicle planning/control and the device/interiors design. The author's final assessment emphasized the insufficient number of strategies able to minimize the MS phenomenon. Further, contribution was then proposed in [16], where the factors of motion sickness were directly linked to specific characteristics of autonomous vehicles, with the already discussed idea of describing main strategies to minimize discomfort from both the device and vehicle control point of view.

More recently, a well-structured yet comprehensive work was the one proposed by Zhang et al. [18], where a better understanding of the mechanism behind MS was portrayed as well as an analysis of the main frequency-related characteristics along the longitudinal, lateral and vertical direction of motion. Moreover, the dissemination proposed the measurement and detection analysis dedicated to already known quantifying techniques. Interestingly, when approaching various mitigation methods, the authors, besides describing vehicle control and human-centric factors (visual-,auditory-,olfaction- based mitigation), underlined the relevant interaction between passenger's and vehicles' environment. However, it is essential to observe how motion planning strategies were introduced as vehicle-centric factors, thus not being related to the evoked passenger's motion. In particular, head motion has been the subject of various studies because of its relationship with the total level of perceived discomfort. Notably, Papaioannou et al. [21] emphasized the importance of employing an advanced human body, which encompasses head motion, to avoid underestimating comfort-related metrics.

Being able to acquire head position and orientation as measurable quantity, can deeply affect the value of motion sickness to be fed into motion planner's objective

function and this possibility has represented an essential theme to be still added to the overall workflow of motion sickness evaluation and mitigation. In this context, because passenger motion is direct consequence of vehicle's behavior, its states should be acquired. Therefore, the vehicle state sensing/estimation phase can be considered as a prerequisite for the subsequent passenger state estimation stage, implying that a relationship (e.g. transfer functions or physical models, see Chapter III-A) must exist between the two steps. As a consequence, as the accuracy and the number of vehicle states increase, higher computationally demanding and precise passenger formulations can be employed. Furthermore, the investigation of Zhang et al. [18] involved the description of current research developments including the lack of studies on multiple direction coordination, while introducing future trends as high precision driving simulation, fully integrated cockpit and comprehensive framework for MS mitigation based multi-sensors development. This latter concept can be described as multi-level observer's structure where both vehicle and passenger's state should be measurable in order to fully control vehicle's behavior. Therefore, as the level of automation increases, the design of the vehicle control structure has to rapidly adapt. From a vehicle control point of view, comprehensive solutions include emerging fields such as integrated vehicle control structures [25], [26], [27], [28], [29], [30], [31], [32], [33], multi-actuated [34], [35], [36] solutions, multi-objective [37], [38], [39], [40], [41], and accurate vehicle controller model design.
Whereas, from a vehicle sensing point of view, existing technologies aim to acquire multiple states and determine the system's parameters through multiple-layer structures [42], [43], [44], [45], [46]. Ultimately, future vehicles will require a complete redesign to achieve optimal performance, safety, and comfort, as well as the need to adapt current methodologies and develop a newer framework. Nevertheless, the analysis of the reviewed literature reveals a lack of structured studies that simultaneously address comfort optimization through MS mitigation and vehicle performance enhancement.

This work aims at guiding the reader from enabling onboard technologies to the necessary trade-offs, regarding the integration of physical sensing with advanced virtual modeling, while carefully balancing accuracy, robustness, and real ECU constraints shaping real-world control frameworks, moving from the traditional modular inadequate vehicle-centric approaches to next-generation architectures. The paper argues that only a clear definition of holistic control can serve as the design compass for future autonomous vehicles, with the decisive shift lying in explicitly modeling the human-biomechanics, physiology, comfort, cognition, as a core system element: transforming the human-vehicle integration layered complexity of requirements into a coherent multi-objective framework; and it culminates in a definition of a holistic control paradigm for autonomous vehicles.

The paper is structured as follows: Section II introduces the framework of vehicle onboard technologies with current constraints and opportunities, and demonstrates the limitations of current incremental approaches and the inevitability of pursuing the holistic paradigm; Section III presents the paradigm shift toward holistic approaches enriching vehicle internal states with necessary passenger estimation; Section IV details the path to holistic framework with feasibility analysis; Section V outlines future research directions; and Section VI provides conclusions.

II. EVOLVING LANDSCAPE OF VEHICLE ONBOARD TECHNOLOGIES

The modern automotive industry is experiencing an unprecedented transformation driven by the convergence of multiple technological and market forces [47], [48], which push toward a fundamental reshape of vehicle onboard technologies and a necessity of a systematic critical trade-offs analysis [49]. The key drivers of this transformation include:

- Physical to virtual sensing transition: increasing necessity to augment or replace hardware-based sensing with model-based virtual sensing approaches while preserving accuracy and robustness within computational and ECU constraints [50], [51];
- System boundary expansion: growing requirements for interaction with external systems including V2X communications [11], energy efficiency optimization [9], and environmental emission control [8];
- Market and regulation differentiation: diverse requirements and expectations across different vehicle categories, mobility modes, and user demographics [52].

These fundamental drivers collectively reveal that traditional integrated approaches are reaching their architectural limits, and necessitate a paradigmatic shift toward holistic frameworks that can orchestrate multi-domain optimization while maintaining real-world feasibility [27], [30]. The technical foundation underlying this transition toward holistic frameworks rests fundamentally on advanced sensing and state estimation capabilities that can support reliable physical-based approaches aimed at multi-subsystem coordination.

The importance of a complete sensing framework has been widely recognized in the field of precisely controlled vehicle behavior [53]. The transition from physical to virtual sensing represents a fundamental trade-off in modern vehicle architectures [54]: physical sensors provide direct measurements but are subject to cost, packaging, and reliability constraints; while virtual sensors, based on mathematical models and sensor fusion algorithms, can provide equivalent or superior information at reduced hardware cost, but require sophisticated algorithms and precise calibration [45]. This trade-off becomes critical when considering market segmentation: premium vehicles may accommodate extensive sensor suites, while mass-market vehicles demand cost-effective virtual sensing solutions that maintain acceptable

TABLE 1. List of Symbols with SI units and Acronyms.

Symbol	Unit (SI)	Description	Acronym	Description
V_x	m/s	Longitudinal velocity	AV	Autonomous Vehicle
V_y	m/s	Lateral velocity	MS	Motion Sickness
a_x	m/s^2	Longitudinal acceleration	AD	Automated Driving
a_y	m/s^2	Lateral acceleration	SBW	Steer-by-Wire
a_z	m/s^2	Vertical acceleration	AFS	Active Front Steering
k_{ij}	–	Tire slip ratio	ARS	Active Rear Steering
ω_x	rad/s	Roll rate	DD	Distributed Drive
ω_y	rad/s	Pitch rate	EV	Electric Vehicle
r	rad/s	Yaw rate	RT	Real-Time
$\dot{\omega}_x$	rad/s^2	Roll acceleration	TV	Torque Vectoring
$\dot{\omega}_y$	rad/s^2	Pitch acceleration	NN	Neural Network
$\dot{r}$	rad/s^2	Yaw acceleration	KF	Kalman Filter
θ	rad	Roll angle	UKF	Unscented Kalman Filter
ϕ	rad	Pitch angle	EKF	Extended Kalman Filter
ψ	rad	Yaw angle	MP	Motion Planning
X, Y, Z	m	Cartesian vehicle coordinates	PT	Path Tracking
ω_{ij}	rad/s	Wheel angular velocity	ML	Machine Learning
μ	–	Road friction coefficient		
C_f, C_r	N/rad	Front and rear cornering stiffness		
M_x	N·m	Rolling moment		
M_y	N·m	Pitching moment		
M_z	N·m	Yawing moment		
h_{cg}	m	Height of center of gravity		
l_f	m	Distance from CG to front axle		
l_r	m	Distance from CG to rear axle		
F_x	N	Longitudinal tire force		
F_y	N	Lateral tire force		
F_z	N	Vertical tire force		
δ	rad	Steering angle		
V_{wheel}	m/s	Wheel speed		
T_{ij}/M_{ij}	N·m	Torque		

performance levels [55]. In recent years, a great number of research studies have been developed toward estimating vehicle's state with the highest level of accuracy while insuring cheapest sensor's measurement setup. This mostly resulted in major resources invested in evaluating variables (β, V_y) to describe vehicle's lateral/handling behavior to feed stability controller [56], [57]. However, the possibilities that derive from state estimation techniques and sensor fusion are almost unlimited and only few works refer to complete or ''holistic'' frameworks to evaluate the totality of vehicle's states.

Although some reviews on the topic have been published [45], [54], [58], [59], [60], [61], comprehensive investigations into complete vehicle state estimation solutions, propaedeutic to holistic approach, are still lacking. For that purpose, the authors collected and organized the recent literature works containing the keywords ''holistic'' or ''comprehensive'' in Table 2. Three major categories can be identified, although the number of works is limited; those include: vehicle+road, vehicle+driver and vehicle+parameters estimation.

Furthermore, most of the works rely on simulation data for validation, thus their applicability to real-world should be investigated and demonstrated in future works. Regarding the state estimation methodologies, Kalman Filter (KF) is indeed the most employed, as reported in [45]; however, in scenarios where the model-based framework requires the preliminary determination of parameters, KF can be augmented by machine learning techniques (RLS) [62], [63], [64].

In the demanding context of accurately evaluating vehicle handling performance aimed at improving safety, it is essential to sense tire state. Although major works employ Pacejka/Dugoff/linear tire models (a detailed overview can be found in Table 1 [60]), they rarely take into account the modified tire's behavior due to temperature, pressure and wear effects. The necessity of tire thermodynamics knowledge for simulation applications has been widely established in [65] and [66], where the authors demonstrated improved estimation accuracy when compared to traditional techniques. On the other hand, when referring to passenger applications, tire wear becomes a crucial issue both for safety- and environmental-related aspects [67]; for that purpose, great emphasis is placed on developing accurate formulations to understand and predict the wear phenomena [68]. At the current stage, only limited amount of works take advantage of the estimated knowledge of tire wear for control-related applications [3], [12].

The algorithms' computational requirements versus ECU hardware availability trade-off represents perhaps the most stringent constraint in automotive applications [69]. Modern vehicles typically operate with distributed ECU architectures where computational resources are allocated across multiple domains (powertrain, chassis, body, infotainment) [55], whereas the transition toward holistic framework will require either centralized high-performance computing platforms or sophisticated distributed algorithms, able to coordinate across ECU boundaries while maintaining real-time constraints and fault tolerance [70], [71]. Indeed, from a design point of view, employing different state estimation techniques leads to various architectures. The adoption of such structures is more frequent when combining parameter and vehicle estimation subsystems and has been identified as ''dual'' or ''cascaded'' structure. Some authors use a less explicit representation (Fig. 1, Fig. 2) while others distinguish the prediction from the correction phase (Fig. 3) of the typical KF structure. The only difference can be found in how the two subsystems are designed to interact with each other (for the sake of simplicity, the authors used red arrows in each image to highlight their different interactions).

Other architectures involve the road estimation block which shares information with the state estimation (Fig. 4), while feeding a prediction model. This latter approach is also presented in vehicle only structures as depicted in Fig. 5; in this context the adoption of different filters oriented to estimate various vehicle-related variables is also displayed by Fig. 6.

In summary, as the holistic state estimation suggests the mutual use of both vehicle, road and parameter estimation modules, the real issue involves defining a structure that can comprehensively manage all the interactions. To this purpose, a first example in 2017 is summarized in Fig. 7 and later in Fig. 8. This latter setup suggests the adoption of combined estimation techniques which improve the estimation accuracy by leveraging the advantages of various formulations (both Kinematic, model-based and data-driven state estimation techniques) and has been widely investigated in [45].

For sake of completeness, the current overview does not take into account future scenarios where the knowledge of other traffic participants' motion is required. This topic is equally relevant to the previous vehicle-only investigation as Tian et al. [58] suggest.

Market requirements across different vehicle categories and mobility modes further complicate the optimization landscape and cannot be effectively addressed through currently available onboard frameworks [52], [79]: luxury vehicles prioritize comfort and user experience, requiring sophisticated comfort monitoring and adaptive behavior [80]; commercial vehicles emphasize efficiency and predictability, demanding robust operation across diverse conditions [81]; shared mobility services require optimization for multiple user preferences and usage patterns [22]. These diverse requirements cannot be addressed through monolithic solutions but necessitate adaptive frameworks capable of reconfiguring their optimization priorities based on context and user preferences.

From the current analysis, it is clear that, although there is a critical need for a full state vehicle estimation

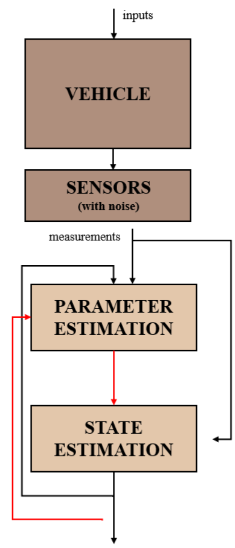

FIGURE 1. Vehicle and parameter estimation architecture, adapted from [72].

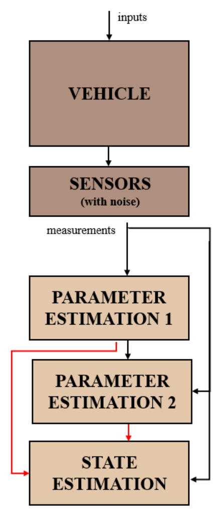

FIGURE 2. Vehicle and parameter estimation architecture, adapted from [73].

framework, its adoption is far from being integrated in real-world applications. The major gaps/limits have been here summarized:

- Applicability to different vehicle configurations and for different sets of sensors: the framework has to meet market's requirement by being not only compatible with various vehicles (and their operating conditions), but also the required measurement signals have to be provided by standard set of sensors;
- Fault tolerance: originally related to controller's design, this feature has been portrayed as essential in different surveys;
- Real system validation: most of the research works have been validated through simulation platforms and without

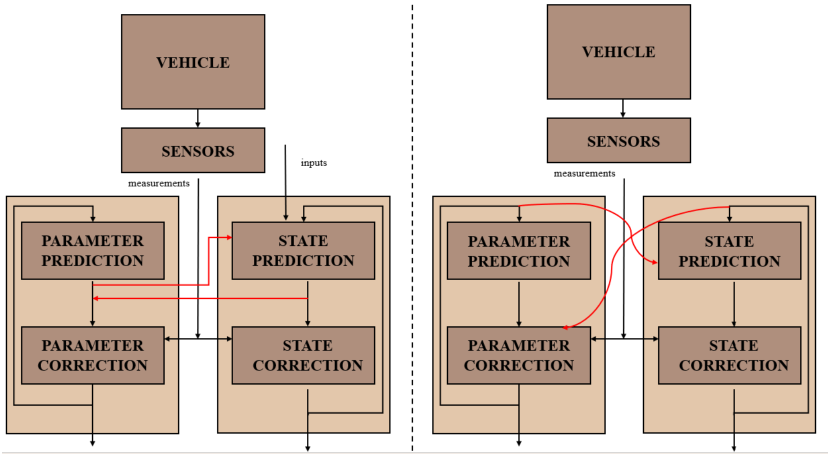

FIGURE 3. Vehicle and parameter estimation architecture. Left image adapted from [46], right from [43].

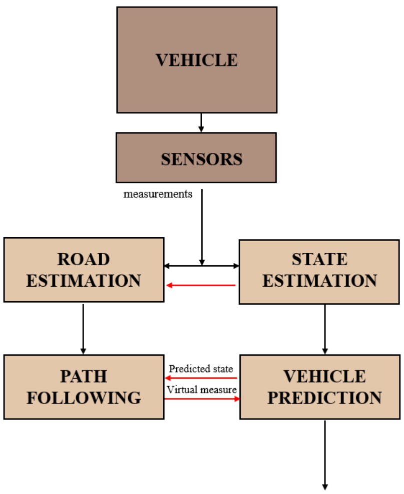

FIGURE 4. Vehicle and road estimation architecture, adapted from [74].

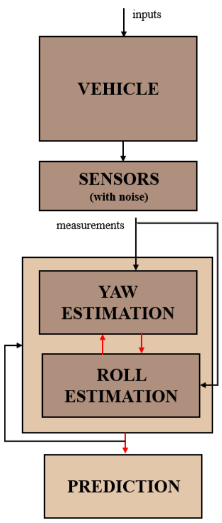

FIGURE 5. Vehicle state estimation architecture, adapted from [75].

using measurements coming from real sensors, thus often neglecting signal noise and disturbance effects;
- More accurate vehicle models: This concept is already explained when referring to model-based techniques which require higher DOFs models to portray the states of a complex nonlinear vehicle. Less simplification implies more accuracy and reliability in various scenarios;
- Hardware: It is easy to notice that as the complexity of the architecture increases, the needed platform should adapt accordingly, thus leading to solutions that have to balance computational effort and cost as they need to represent affordable solutions for the market [24], [70].

The convergence of these technological drivers and market forces leads to an inevitable conclusion: the holistic approach emerges not as an incremental improvement, but as the only viable architectural paradigm capable of orchestrating the complex interactions between vehicle dynamics, passenger states, environmental constraints, and external system interfaces [28], [29], [82], [83].

However, the transition to holistic frameworks requires more than technological advancement—it demands a precise, operational definition of what constitutes "holistic" control and clear engineering requirements for its implementation [84]: this definition must encompass not only the technical aspects of multi-domain optimization but also the fundamental paradigm shift toward human-centric design, where passenger comfort, user experience, and adaptability to individual preferences become primary optimization objectives rather than secondary constraints [85], [86].

State-of-the-art sensing architectures are commonly characterized by a vehicle-centric approach organized in multiple layer, often working simultaneously. Interestingly, this latter feature can be regarded as a preliminary scheme that is expected to evolve as additional subsystems are progressively

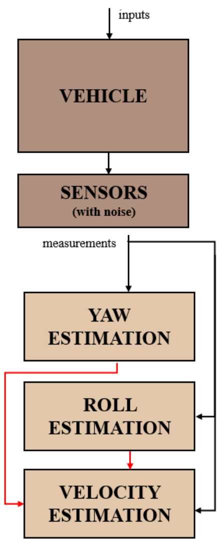

FIGURE 6. Vehicle state estimation architecture, adapted from [76].

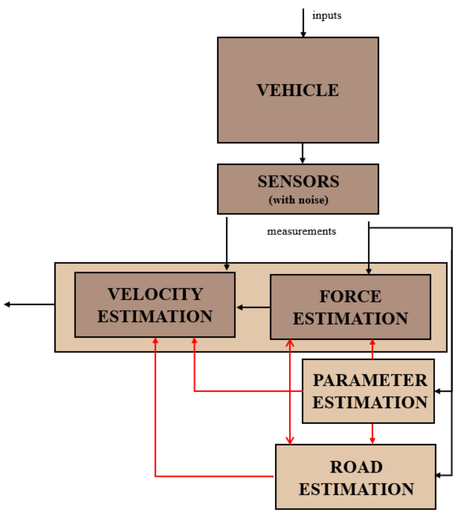

FIGURE 7. Vehicle, parameter and road estimation architecture, adapted from [77].

integrated. In fact, sensing frameworks primarily serve the purpose of providing control logic with the required states; hence the adoption of multiple layers offers several advantages. On the one hand, to overcome current limitations, modular structure implies better applicability to different scenarios (vehicles and sensors) while parallel simultaneous layers add redundancy (fault tolerance) and enable parameter refinement. On the other hand, these architectures lay the groundwork for estimating states associated with heterogeneous subsystems [51], such as passenger dynamics or fuel efficiency. The evolution toward holistic frameworks represents the natural progression of this multilayer approach, extending system boundaries to explicitly include human factors, environmental interactions, and external system coordination within a unified optimization framework [87], [88].

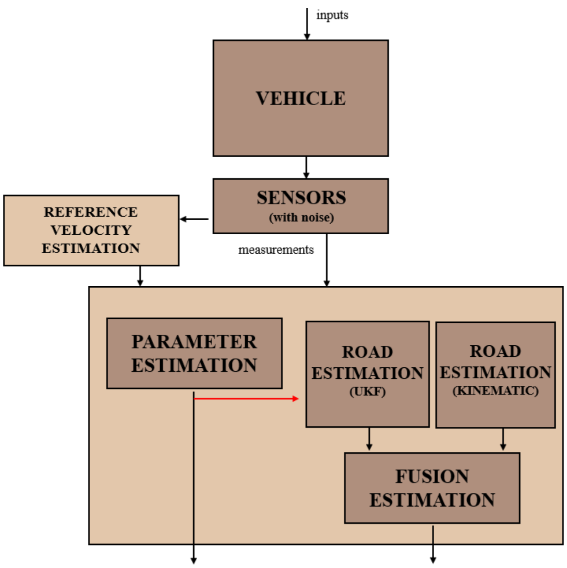

FIGURE 8. Vehicle, parameter and road estimation architecture, adapted from [78].

III. BEYOND INTEGRATION: TOWARD UNIFIED VEHICLE-HUMAN SYSTEMS

State estimation in modern vehicles already requires integrating heterogeneous sensor networks with both model-based and data-driven methods, and this becomes even more critical when the goal is the design of comprehensive architectures able to couple vehicle, road, and passenger state estimation, moving beyond traditional vehicle-centric approaches. The inclusion of the human factors in onboard logics represents a fundamental paradigmatic addition, still without a standardized pipeline and under investigation in diverse academic and R&D institutions: therefore, a specific focus on possible modeling, sensing and estimation techniques concerning the human MS, employable in the actual and future vehicle development, with particular emphasis on estimation methods and bio-sensing approaches, is dedicated in this section.

A. PASSENGER SYSTEM SENSING

Multiple theories seek explanations for why MS occurs, ranging from sensory conflict theory [19] that identifies as MS causes the mismatch between perceived and expected sensory inputs, to postural instability theory [96] which attributes the insurgence of MS to situations when the central nervous system (CNS) is not able to properly integrate sensory signals from visual, vestibular and proprioceptive systems leading to a loss in maintaining muscle balance. In both cases, head motion is a key determinant factor to determine the perceived (dis)comfort, as it has been proven that the head shows substantial rotations in response to seat translational excitations [97], [98], [99]. The transmission of motion from seat to head is strictly related to seat compliance and posture [98].

TABLE 2. Holistic vehicle state estimation works found in literature. Recent surveys on the topic are also included. ("S"=Simulation,"E"=Experiments, "R"=Real world implementation).

Category	Objective	Method	Measurements	Validation	Gaps	Title	Date
Vehicle	Vx, Vy, k_{ij}, Vy_{ij}	KF	Vx_{gnss}, Vy_{gnss}, r	S, E		[89]	2024
	$X, Y, Vx, Vy, \psi, r, \omega_{ij}$	Switching observer (based on two models)	ay, vx, suspension displacement	S		[75]	2009
Vehicle and road	F_{ij}, V_{ij}, V, bank/grade road angle	UKF (Fx_{ij}), UKF (for lateral), observer (θ, ϕ)+ Lugre tire model (Vx/Vy)	$ax, ay, r, az, \delta, \omega, \dot{\theta}, \dot{\phi}, T_{ij}$	S, E	Combined bank and grade, using μ information for road angle estimation, considering camber angle, estimation of wheel torques, road classification in long direction, lat. dynamics with combined slip models	[77]	2017
	$Vx, r, ax, \dot{r}, \mu$	Vehicle filter (KF) + road geometry filter (KF)	δ, Vx, ax, r, vision system: curvature,slope and distance to lane mark	S, R	Integration of GPS (for road geometry estimation)	[74]	2014
	β, r and μ	Interacting multiple model (IMM) algorithms, mode probabilities and states based on EKFs	ay, r	S	More complex vehicle model	[90]	2006
	Vx, m, road slope	Multi dimensional information fusion fuzzy rules (vx), RLS (mass), interactive multiple model (KF based) (road slope)	$V_{wheel}, F_x, V_{ref}, ax$	R		[78]	2022
	X_g, Y_g, V_g, Vy_g, $Z_g, Vz_g, \theta_{absolute}, \phi_{absolute}, \psi_{absolute}$, road bank angle, road grade angle,ψ	UKF	Suspension displacements sensors, gps and ins	S		[91]	2015
Vehicle and driver	Driver and vehicle (velocity, position, orientation) states	KF to estimate observable parameters (vehicle level), rule-based estimation and hidden Markov model		S	Large set of manevuers, modelling of swarms of vehicles (convoys, teams)	[92]	2011
Vehicle and parameters	Vx, r, β under time-varying model parameters	Strong tracking H-infinity EKF	ax, ay, δ	S	Adaptive adjustments of model parameters	[72]	2023
	β, Vy, C_f, C_r	Dual extended EKFs	r, vy	S, R		[46]	2021
	C_f, C_r, trailer's M_x, M_z and h_{CG} and states(β, ψ, θ trailer and tractor)	Dual Extended KF, KF	V_x of trailer and tractor, δ on front/middle/rear axle of each unit, $r_{trailer/tractor}$	S, R		[73]	2010
	State and parameter to evaluate rollover index (θ and h_{cg} estimation)	Sensor fusion + nonlinear dynamic observer, RLS for h_{cg}	Tilt angle sensor, ay, gyroscope	S, E		[93]	2011
	States (β, vx, θ and grade) and parameters (C_f, C_r, understeer gradient, roll stiffness)					[76]	2004
	$vx, \beta, r, \theta, \dot{\theta}, \theta, \phi_{global}, \omega_{ij}$, grip, C_f, C_r	EKF	ax, ay, r, ω_{ij}	S, E	Introduction of GPS, parameter estimation	[94]	2022
	Fz_{ij}, lf, h_{CG}	Cascaded dual EKF	ax,$T_{ij}, \omega_F, \omega_R, az_F, az_R$	S	Full vehicle model and estimation of state and parameters for different sensors options	[43]	2013
	Vx, r, β, m	Dual H-infinity EKF	δ, ax, ay	S	Complex scenarios, introduction of road-bank angle	[44]	2021
Survey	Vehicle, road, motion of other vehicles and pedestrians estimation techniques	EKF, UKF, CKF, observer-based, data-driven, V2x-based			Robust state estimation with model uncertainty, multimodal state estimation with environmental impact, fault tolerant state estimation considering signal droupout and cyberattacks, effective public evaluation platform	[58]	2025
	Vehicle state estimation	KF, kinematic, observer, data-driven, optimization based			Range of applicability (connected AVs), coupling problems, unknown inputs, stability and robustness, RT issues	[59]	2018
	Vehicle state estimation	Kinematic, Dynamic (KF, Observer) and data-driven approaches			Range of applicability (AVs), nonlinear dynamics estimation	[60]	2019
	Vehicle-trailer state and parameter estimation	Model-based (kinematic, dynamic) and non-model based			Limited coverage, model simplification, severe assumptions, complex vehicle model	[95]	2022
	Human motion, objective detection, sensors used in AVs, vision based state estimation	Human motion (Physics, Pattern, Planning-based), Vehicle (KF, PF), road (NN, Bayesian, SVM)				[54]	2022
	Vehicle state estimation in AVs	EKF,IEKF,CRT			Alternative algorithms for state estimation and hardware to implement them	[61]	2017
	Hybrid models for vehicle state estimation	KF (EKF,UKF,CKF), NN and hybrid KF+NN			Hybrid model formulations	[45]	2023
	Vehicle, road, tire, parameters estimation	Kinematics, model-based and data-driven approaches			Intelligent tires and load sensing bearings	[50]	2018

Moreover, certain physiological signals have been associated with passenger distress, highlighting their importance in identifying predictive markers that can anticipate the onset of motion sickness.

Therefore, to effectively mitigate motion sickness, it is crucial to estimate body posture, head accelerations and physiological signals, allowing real-time personalized adjustments to vehicle motion.

Three primary approaches have been explored in the literature: i) sensors, to measure the physiological signals related to passenger distress; ii) biomechanical models, which provide a more detailed representation of human body dynamics in response to vehicular motion and, iii) transfer function-based methods, which characterize dynamic relationships between inputs (e.g., vehicle accelerations) and outputs (e.g., head motion).

1) EXPERIMENTAL EQUIPMENT

Many recent studies aim to improve passenger safety and comfort, resulting in the need for systems that can detect motion sickness. One promising approach involves using a combination of wearable sensors or medical devices to detect physiological signals and identify early signs of discomfort, thereby avoiding the inaccuracy of subjective evaluations of motion sickness and comfort/discomfort. Researchers have used multiple devices, traditionally employed in the clinical field, to obtain an objective assessment aimed at accurately measuring and predicting motion sickness; in most cases, researchers have used electroencephalogram (EEG), electrocardiograph (ECG), and heart rate or heart rate variability (HRV), galvanic skin response (GSR), and electrodermal activity (EDA), or a combination of these.

- **Electroencephalogram (EEG)**: EEG is a non-invasive technique that involves the placement of electrodes on the scalp to record the electrical activity of the brain, for the exploration of cognitive processes. EEG waveforms are classified according to their frequency, amplitude, and shape, as well as the sites on the scalp at which they are recorded. The most familiar classification uses the frequency of the EEG waveform (e.g., alpha, beta, theta, and delta) [100]. This signal can measure cerebral alterations when the subject undergoes a motion sickness stimulus, indicating, for example, the sections of the human brain that are most activated. In this context, Henry et al. [101] sought to identify specific cerebral changes associated with the level of car sickness given by the passengers. The results demonstrated that the symptoms evolved with changes in EEG activity, mainly in the areas of the brain involved in sensory integration and found that theta and alpha power in the parietal and occipital regions increased with the severity of car sickness. Furthermore, in [102], the researcher wanted to predict motion sickness, using a Convolutional Neural Network Model, based on dry EEG that can be easily worn in a real driving environment. They found that motion sickness could be accurately predicted within approximately 12s, and even when approximately 10 fewer channels are used, enhancing the practicality of the study. Consistent with the use of machine learning, in [103], a self-organizing neural fuzzy inference network (SONFIN) was proposed to estimate a driver's or passenger's sickness level based on EEG features extracted from specific brain areas. It results in the broadband EEG power responses in the occipital midline brain area being more highly correlated with subjective sickness levels. The alpha and gamma bands of the EEG power spectrum are valid indicators of motion sickness, with an overall performance of the average prediction accuracy of ∼82%.

- **Electrocardiograph (ECG) and Heart Rate Variability (HRV)**: ECG and HR or HRV are fundamental tools for cardiovascular monitoring. The ECG records the heart's electrical activity noninvasively and provides information about heart rhythm, conduction pathways, and potential abnormalities. The typical ECG waveform includes standard components (P wave, QRS complex, and T wave) [104]. The HRV measures the oscillation between consecutive heartbeats (the Inter-Beat Intervals). In this section, we gave an overview of the studies in which these techniques were used and gave major results, including studies where they were combined with other sensors or devices. Motion sickness detection was studied in [105], where the researchers proposed a framework based on physiological signals during on-road driving scenarios. EDA, HR, body temperature, regional blood oxygenation changes, and PPG (Photoplethysmography) signals were chosen. The results indicate that EDA signals and temperature, and HR and temperature, might be suitable inputs to detect motion sickness. However, the HR and temperature are easier to obtain and would be the most efficient input for car sickness detection. Similarly, in [106], the researcher found that HR and perfusion index have a significant relationship with the subjective motion sickness score, suggesting these variables as important predictors of passengers' motion sickness. These studies have revealed that incorporating combined measurements enhances the accuracy of capturing the temporal progression of symptoms using only simple wearable sensors. In continuity with these findings, researchers focused on the HR and its user-friendliness. In this context, Baggiato et al. [107] in their research wanted to assess discomfort using physiological parameters from smartbands, pupillometry, and body motion. Results showed a reduced eye blink rate during discomfort as well as pupil dilation, also after correcting for ambient light influence. Contrary to expectations, HR decreased significantly during discomfort periods, whereas HRV diminished as expected. No effects could be observed for Skin Conductance Level (SCL). Body motion showed the expected pushback movement during the close approach situation. In [108] the HR was collected in combination with EDA, pupil diameter, and eye blinks. These parameters did not show changes when the level of discomfort was low. On the other hand, HR decreased consistently during uncomfortable situations, related to the phenomenon "preparation for action". Pupil diameter increased, and eye blink rate decreased in uncomfortable situations. EDA did not show specific effects. Considering the previous studies and their results, the HR is more convenient than the ECG because of its ease of use. Despite this, many studies considered the ECG and its possible correlation with car motion sickness. In [109] the research focused on the evaluation, in real driving conditions, of the impact of lateral acceleration level and vehicle path predictability on car sickness incidence and severity. An increase in several physiological parameters (from ECG and EDA) was found simultaneously with higher car sickness ratings, demonstrating activation of the sympathetic nervous system, indicating car sickness severity.
- **Galvanic Skin Response (GSR) or Electrodermal Activity (EDA)**: One of the visible symptoms of car sickness is the passenger's sweating, so GSR could be an important indicator. Implementing the GSR using electrodermal activity (EDA) and skin conductance level (SCL) is common. In general, GSR refers to changes in the skin's electrical properties: these changes are driven by the sympathetic branch of the autonomic nervous system, involved in emotion and stress [110]. In the study by Irmark et al. [20], they collected head roll (using an inertial sensor), GSR, and ECG, and modelled the evolution of motion sickness using an adapted model of nausea. Motion sickness did not affect head roll; otherwise, it caused modest variations in the ECG. Motion sickness mostly affected GSR at high MISC levels. However, GSR also rose with time without motion sickness, accompanied by significant dispersion. This aligns with the findings of [111]. They wanted to identify physiological changes that can be the response of the passenger to motion sickness in a real driving environment using wearable sensors to collect heart rate, pulse, respiration, skin temperature, and EDA. Using a regression model, they demonstrated that EDA and pulse were the most relevant features for predicting a higher motion sickness level. In [112] the researchers studied passenger responses to different driving style parameters, collecting GSR, HR, and eye-movement patterns, along with self-reported comfort and anxiety scores. The results show that the presence and proximity of a lead vehicle raised the level of all measured physiological responses, particularly skin response. Furthermore, in [113], the researchers investigated the relationship between motion sickness, EDA, and vehicle state during motion sickness episodes, introducing the cumulative seat rail vibration acceleration (CVA). The main result was that the change rates of longitudinal vibration cumulative value (CVAx) and EDA exhibit robust correlations, signifying their significance

concerning motion sickness severity. In contrast with the previous studies' findings, it was also demonstrated that EDA has no significant correlation with motion sickness. In [114], the research focused on sweating, so they collected the EDA but also information related to the forehead humidity, and only this increased significantly in the high-intensity condition. In continuity with these findings, Smyth et al. [115] demonstrated that although EDA and skin temperature are related to motion sickness, there was a lack of reliability for these measures at an individual level for simulator and on-the-road experimentation.

- **Other biomedical instrumentation**: In the scientific literature, different methods exist compared to the ones previously presented, able to detect the motion sickness level. In [116], the Electrogastrography (EGG, a non-invasive method used to measure the myoelectric activity of the stomach) was used to assess motion sickness. The participants encountered two environments: a straight and less dynamic road and a highly dynamic and curvy road. They found out that the EGG could be a good indicator of motion sickness. Hiemstra-van Mastrigt et al. [117] focused their research on the passenger's perceived comfort using an active seating system consisting of sensors in the backrest that register upper body movements and physiological signal sensors. They used different sensors: HR, and the muscular activity of six postural muscles was measured through electromyography (EMG), showing higher muscle variability and muscle activity for active seating, demonstrating that active seating can increase comfort and well-being.

The detailed review of the studies shows heterogeneous results regarding the use of physiological signals to identify and predict motion sickness. Many devices consistently proved to be valid and reliable, while others yielded more limited or inconsistent outcomes. Additionally, the same type of sensor was sometimes found effective and other times less reliable, indicating potential issues related to methodological differences, experimental setups, or individual differences. Although physiological monitoring can be useful in real-world scenarios, these variations imply that the results must be carefully interpreted. Future research should standardize protocols, validate the results with larger and diverse populations, and clarify the conditions under which specific sensors can produce accurate and reliable predictions.

2) HUMAN BODY MODELING

Human body modeling plays a crucial role in understanding passenger posture and, in particular, the head motion within vehicles, particularly in automated driving scenarios where occupants may adopt unconventional seating positions. Various biomechanical models have been developed to represent human posture and motion, each differing in complexity, application, and computational demand. These models can be broadly classified into four categories:

- **Transfer functions** - Head motion studies can be traced back to 1994 when Paddan and Griffin [118] conducted a series of experiments to investigate the transmission of roll and pitch seat vibrations to the head of seated subjects. During roll seat vibration, head motion primarily occurred in the lateral direction, with significant roll and yaw rotations, while pitch seat vibration induced fore-and-aft motion, vertical motion, and pitch rotation. The results showed that the least head motion occurred when the center of rotation was aligned with the subjects' mid-sagittal plane. The roll head motion decreased as the center of rotation was raised from below to above the seat surface. Conversely, head motion increased with the distance of the center of rotation positioned either in front of or behind the subjects' ischial tuberosities, as well as when the seat was elevated from below to above the center of rotation. Moreover, the authors calculated transfer functions between rotational seat acceleration and the six axes of acceleration at the head. The authors further extended their study in [119], investigating the role of visual systems in head transmissibility, highlighting a difference when comparing results with eyes open and eyes closed. However, it is well known that while negotiating a curve, drivers tilt their heads differently from passengers: the former tilts their heads toward the center of the curvature, while the latter behaves in the opposite way. For this reason, in [120], the authors investigated the differences in head transmissibilities between the two, developing three transfer functions with increasing order. As a result, in their experimental set-up, the authors found out that the highest transfer function order (4th) best fits the experimental results. Nevertheless, none of the aforementioned research investigated the role of the transfer functions aiming at an accurate motion sickness metric estimation. To address this gap, in [21], the authors investigated how the MS metric is affected when calculated with the acceleration of the vehicle, versus the cases where two human body models are used to retrieve the motion of the head and the experimental results. As an outcome, the MS metric is underestimated in the absence of human body model with respect to the experimental case, while the use of a human body model showed reduced deterioration in the estimation. However, the human body model may increase the computational complexity for real-time applications and for this reason, six sets of transfer functions are developed ad hoc, investigating how the translational and rotational accelerations of the seat, influence the head motion. Notably, these transfer function links the following accelerations: i) seat vertical to head vertical and pitch, ii) seat longitudinal to head longitudinal and pitch, iii) seat lateral to head lateral and roll, iv) seat pitch to head longitudinal, vertical and pitch, v) seat roll to head lateral, yaw and roll; and, vi) seat yaw to head yaw. These transfer functions hold the potential to reduce the computational effort of a control strategy, aiming at reducing MS considering head motion.

- **Lumped-Parameter (LP) Models** – These models consist of lumped masses, springs, and dampers, providing a simplified representation of the human body. They are widely used due to their computational efficiency and applicability in assessing biodynamic responses to vibrations. LP models have been extensively studied in the literature to evaluate human body responses to vibrations and other dynamic inputs. For instance, Muksian and Nash [121] proposed a multi-degree-of-freedom (MDoF) LP model for a seated human body, incorporating active forces and nonlinear passive elements. Their model, limited to vertical motion, was validated using sinusoidal seat displacement inputs [121]. Boileau and Rakheja developed a 4-degree-of-freedom (DoF) LP model to represent a seated driver without backrest support, with feet on a vibrating platform and hands on the steering wheel [122]. Bai et al. [123] conducted a systematic study on 4DoF linear LP biodynamic models and found that increasing the number of parameters had minimal influence on model accuracy. They proposed an equivalent simplification method for seated occupants [123]. Akbari et al. developed an LP model of the upper body's sagittal plane to simulate disturbance energy propagation and provide quantitative ride comfort assessments [124].
- **Multibody (MB) Models** – These models consist of articulated rigid segments connected by joints, offering a more detailed description of human motion and posture adaptation. They are commonly employed in studies related to ride comfort and motion sickness assessment. Multibody models (MB) provide a more detailed representation of human posture and motion. Liang and Chiang [125] introduced a 14-DoF MB model to study the biodynamic responses of a seated human body exposed to vertical vibrations. Their model, developed in a 2D sagittal plane, includes five rigid segments connected by bushing elements, representing a seated occupant with backrest support [125]. Cho and Yoon developed a 9-DoF MB passenger model incorporating both longitudinal and vertical DoFs, demonstrating that including backrest support significantly affects the natural frequencies and improves vibration transmissibility predictions [126]. Mohajer et al. developed an intricate 28-DoF MB model integrating seat-human biomechanics and associating root-mean-square (RMS) acceleration with ride comfort, finding strong correlations between ride comfort and vertical/longitudinal vibrations [127]. Wu and Qiu [128] proposed a 16-DoF MB model of a seated human body exposed to combined lateral, vertical, and roll vibrations, including segments for the abdomen, pelvis, thighs, torso, neck, and head. Their study calibrated model parameters to minimize discrepancies between predicted and experimental apparent masses [128]. Guruguntla et al. introduced a 10-DoF vertical biomechanical MB model of the upper body, optimizing parameters to better replicate human response to vibrations compared to lower DoF models [129].
- **Finite-Element (FE) Models** – These models allow for high-fidelity biomechanical analysis, capturing soft tissue deformations and pressure distributions. However, they require significant computational resources, making them more suitable for crash simulations and injury prediction. Finite-element models offer the highest level of detail, capturing complex interactions within the human body. Iwamoto et al. [130] developed the Total Human Model for Safety (THUMS), an FE model designed for injury prediction in crash scenarios. THUMS includes bones, ligaments, tendons, and soft tissues, modeled with over 80,000 elements [130]. Östh et al. extended THUMS by incorporating feedback-controlled muscle activation to simulate anticipatory postural responses, improving occupant kinematics predictions during autonomous braking scenarios [131]. Borst et al. further enhanced human body modeling by developing a muscle geometry and parameter dataset from post-mortem human subjects [132]. Meijer et al. leveraged the MADYMO [133] human model to improve neck modeling based on Borst's dataset, enhancing predictions of anterior-posterior frequency perturbations [134]. Desai et al. [135] introduced a computationally efficient human MB model (EHMB), validated through frequency-domain analysis of 3D vibration transmission from seat to pelvis, trunk, head, and knees. The model interacts with FE and MB backrest models using various contact representations [135]. Desai et al. extended the EHMB by incorporating postural control mechanisms, including joint angle control for reflexive stabilization and head-in-space control to minimize head rotations [136]. Happee et al. validated the EHMB's ability to capture translational and rotational motion, later coupling it with sensory integration models to estimate motion sickness accumulation [137].

It becomes clear that the selection and deployment of a selected human model within possible onboard framework depends critically on computational constraints and control loop frequencies:

- Transfer functions entail the lowest computational demand, making them ideal for real-time implementation even in high-frequency control loops and suitable for basic motion sickness prediction, but their calibration requires extensive experimental;
- Lumped-parameter models offer the computational efficiency necessary for real-time implementation in mid-frequency control loops (20-50 Hz), making them suitable for basic motion sickness prediction and comfort optimization;
- Multibody models provide enhanced accuracy for passenger motion prediction but demand greater computational resources. These models can be deployed

in predictive control frameworks where computation can be distributed across prediction horizons, or in hierarchical architectures where detailed biomechanical analysis operates at slower time scales to inform faster control loops;
- Finite-element models, while offering the highest fidelity, are primarily suited for offline optimization of seat design and cabin layout rather than real-time control applications. However, their results can inform parameter selection and constraint definition for simpler models used in online control.

B. FROM MOTION TO MS METRICS: ASSESSING DISCOMFORT

An accurate assessment of motion sickness is crucial to mitigate discomfort in automated vehicles. Over the years, a variety of metrics have been developed to quantify the severity and likelihood of motion sickness symptoms under different dynamic conditions. The most widely used include the Motion Sickness Dose Value (MSDV), which estimates accumulated discomfort based on acceleration inputs; the Motion Sickness Incidence (MSI), which predicts the percentage of affected individuals over time; and, the Misery Scale (MISC), which provides a continuous assessment of symptom severity. Each metric captures a distinct dimension of the motion sickness phenomenon, and their selection is critical depending on the objectives of a given study, as they are suited to specific experimental or modeling contexts. More in detail, the MSDV is defined as follows:

$$\mathrm{MSDV}_z = \sqrt{\int_0^T \left[a_{z,w}(t)\right]^2 dt} \tag{1}$$

where $a_{z,w}(t)$ is the frequency-weighted vertical acceleration, using filters designed to cut-off the acceleration components which are not involved in the insurgence of motion sickness as suggested in [138]. The MSDV is further extended to longitudinal and lateral components as in [139]:

$$\mathrm{MSDV}_{xy} = \sqrt{\int_0^T \left[a_{x,w}(t)\right]^2 dt} + \sqrt{\int_0^T \left[a_{y,w}(t)\right]^2 dt} \tag{2}$$

where $a_{x,w}(t)$ and $a_{y,w}(t)$ are the frequency-weighted acceleration, based on filters proposed in [140] and [141].

An alternative formulation is the one used in [142], where:

$$\mathrm{MSDV}_{xy} = \sqrt{\int_0^T \left[a_{x,w}^2(t) + [a_{y,w}^2(t)\right] dt} \tag{3}$$

A more comprehensive formulation is finally presented in [21], where the MSDV encompasses all translational and rotational accelerations:

$$\mathrm{MSDV}_{tot} = \sqrt{\sum_i \int_0^T \left[a_{i,w}^2\right] dt} \tag{4}$$

where the subscript $i = x, y, z, \varphi, \theta, \psi$ indicates the acceleration axle (i.e. $a_\varphi = \dot{\omega}_x$, $a_\theta = \dot{\omega}_y$, $a_\psi = \dot{r}$).

Another widely used metric for motion sickness assessment is the *Motion Sickness Incidence* (MSI) [143], [144]. The MSI represents the percentage of subjects that would vomit after 2 hours of exposure to a given motion stimulus. Its computation is based on the *Subjective Vertical Conflict* (SVC) theory, which quantifies the conflict between the sensed and expected vertical [19], [145]. This conflict is represented by the variable Δv, which denotes the difference between the sensed vertical and the internal estimate of verticality maintained by the central nervous system. The MSI is then derived from the time integral of a non-linear function of Δv, typically using a second-order filter and a Hill function to model the emetic response [19]. Several models for MSI evaluation can be found in the literature. For instance, some authors consider the visually perceived rotational velocity as an additional input to the computational model [146], [147], [148].

A further metric is the *Misery Scale* (MISC) [149]. The MISC is a subjective rating scale ranging from 0 to 10, where 0 indicates no symptoms and 10 corresponds to vomiting. Although the MISC is a verbal scale and typically obtained through self-reporting, it can also be estimated computationally from the same sensory conflict signal Δv used in the MSI model [150], [151]. This allows for a more continuous and descriptive evaluation of discomfort during motion exposure, particularly when vomiting does not occur but relevant symptoms are still present.

In the following, the computational models for both MSI and MISC are presented in Figure 9. Regarding the MSI model, the required inputs are the linear accelerations and angular velocities of the passenger's head, which can be computed based on the aforementioned methodologies in Chapter III-A. These inputs are processed to compute the sensory conflict Δv, which is then passed to a Hill function. The Hill function provides an intermediate output h, which is processed in the final transfer function to compute the MSI. The result is expressed as a function of P, the maximum percentage of people likely to experience motion sickness for the given inputs, and a characteristic time constant τ_1 (see Figure 9a).

Similarly to the MSI computation, the parameters of the model can be tuned appropriately to obtain the MISC (see Figure 9b).

In the three subsequent models (Figures 9c-e), the processing of the sensory conflict differs from the previous cases. Specifically, all three include two transfer functions representing the fast and slow dynamics of the system; however, they differ in terms of input and output signals processing:
- Figure 9c: the sensory conflict is used as the input, and the final output u_o is raised to a power M_{AP};
- Figure 9d: the input is the sensory conflict raised to a power M_{BP}, and the output u_o corresponds to the MISC;
- Figure 9e: the sensory conflict is processed through the Hill function, and the final output u_o corresponds to the MISC.

Finally, for the sake of clarity, Table 3 summarizes the vehicle inputs required, the sensors capable of providing these inputs, the estimated vehicle and passenger states, the need for model tuning, and the relevant applications found in the literature for each metric described above.

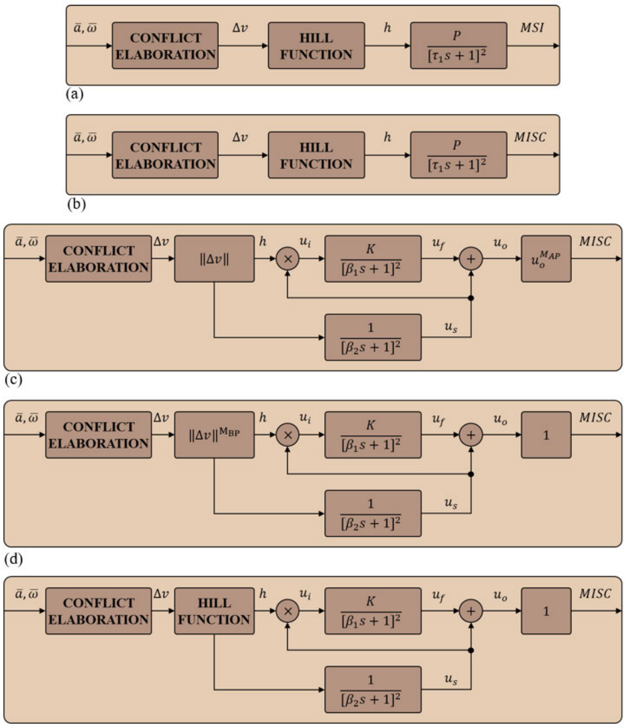

FIGURE 9. Comparison of MS metrics models: (a) MSI model; (b) MISC - MSI based; (c) MISC - AP model; (d) MISC - BP model; and (e) MISC - Oman Hill.

C. INTEGRATION OF MS MITIGATION STRATEGIES

Since motion sickness is a subjective and multi-factorial phenomenon, a promising direction is the simultaneous deployment of complementary techniques, exploring the potential of integrating multiple approaches.

When MS onset is detected, the controller should dynamically adjust vehicle motion parameters, potentially sacrificing minor performance margins to prioritize passenger comfort through adaptive weighting mechanisms. For instance, a priori prevention through trajectory planning optimization that minimizes acceleration profiles known to induce motion sickness involves incorporating MS metrics (MSDV, MSI, MISC) directly into the path planning objective function, enabling proactive comfort optimization before symptoms manifest.

Active seat control and cabin management represents a further mitigation layer, with seat actuators and environmental controls responding to both predicted and detected discomfort levels, but this requires bidirectional communication between passenger state estimation and cabin actuator control systems, exemplifying the cross-domain integration fundamental to holistic approaches.

IV. THE PATH TO HOLISTIC FRAMEWORK

Since the evolution from integrated to holistic control involves multi-objective cost functions, modular and adaptable architectures, and explicit inclusion of comfort and user states, this section reviews interdependent challenges across a wide range of research fields, discussing the requirements for real-time implementation and adaptation of recent control strategies. In healthcare, for example, researchers have analyzed and clarified the concepts of holistic nursing and medicine, which address the physical, emotional, social, and spiritual dimensions of patients, considering how each of these aspects interrelates and contributes to overall well-being [85], [86]. In aerospace and systems engineering, the holistic approach is used in value-driven design, which considers customer value, system resilience, and lifecycle performance simultaneously instead of focusing narrowly on requirements [84]. In [87], the authors present a holistic cyber-physical management framework for industrial wireless control, proposing to optimize both plant control and network reliability to increase system resilience while minimizing resource consumption. More applications in industrial settings are suggested in [88], where the authors propose a holistic approach to identify optimal solutions for efficient processing, given the strong interrelation between energy consumption and material resources (e.g., water). A recent application of this approach can be found in [154], in which the holistic approach refers to an integrated, multi-layered methodology for evaluating and ensuring the safety of battery energy storage systems (BESS). Further research uses a holistic approach to improve the safety of battery energy storage systems by combining currently adopted approaches, such as battery cell testing, lumped cell mathematical modeling, and calorimetry [154].

These varied achievements establish a compelling precedent: holistic methodologies hold the potential to reshape complex engineered systems. In domains characterized by multi-layered interactions and evolving requirements, such as those involving sensing, actuation, human factors, and dynamic environments, a holistic perspective naturally emerges as a valuable approach. The integration of multi-objective trade-offs and user-centric considerations within this framework facilitates the development of more adaptable, robust, and context-aware control strategies, paving the way for further exploration of its relevance in increasingly sophisticated applications, including advanced vehicle systems.

A. HOLISTIC IN VEHICLE CONTROL

This paragraph investigates the definition of holistic control through literature work and the adoption of common (widely employed) structures or methodologies. Alarcon et al. in 1995 underlined the necessity of an integrated control system which consists of layers of interacting elements [83]. This work designed a conceptual framework for the management

TABLE 3. Motion Sickness metrics related with passenger and vehicle's state estimation techniques. Besides mentioned symbols, I_{color} is the color image in the i-th frame captured by a human head attached camera; a_x^v, a_y^v, a_z^v are the visually perceived longitudinal, lateral and vertical accelerations.

MS metrics	Input	Sensors	Vehicle state estimation	Passenger state estimation	Tuning	Application
MSDV [138]	a_x, a_y, a_z	IMU	-	-	No	MP [142], [152] long. + lat. PT [139] long. + lat.
MSDV [21]	$a_x, a_y, a_z, \dot{\omega}_x, \dot{\omega}_y, \dot{r}$	IMU	$\dot{\omega}_x, \dot{\omega}_y, \dot{r}$	-	No	-
MISC [149] / MSI [19]	$a_x, a_y, a_z, \omega_x, \omega_y, r$	IMU		Transfer function	Yes	-
				Multibody	Yes	-
		IMU, Depth camera		Neural Network - Machine Learning	Yes	-
MSI + vision [146], [153]	$a_x, a_y, a_z, \omega_x, \omega_y, r$, (a_x^v, a_y^v, a_z^v) [146], I_{color} [153]	IMU, camera		Transfer function	Yes	-
				Multibody	Yes	-
		IMU, camera, Depth camera		Neural Network - Machine Learning	Yes	-

and control of industrial installations. The issue of being able to coordinate individual control units (pursuing their own actions) was then investigated by Axelsson et al. in [82] where the holistic term included: the functionality of the vehicle system (rather than its subsystems), the inclusion of embedded system and physical environment and the hardware/software designed as a whole. Indeed the adoption of a holistic framework was seen as a solution to the integrated control problem which was in those years being intensively studied and to which some control structures were proposed [26], [29], [155]. However, as can be seen from the following articles in the field of vehicle control, the use of the term "holistic" has become vague and generally difficult to interpret, both from an application perspective and from a methodological standpoint.

The holistic concept began to be frequently associated with either multi-objective or multi-actuated control. In general, the former refers to scenarios in which an optimal decision must be made while balancing two or more conflicting objectives, whereas the latter involves the possibility of executing a specific control action using multiple actuators. To give the reader a more complete overview, the authors summarized the analyzed articles in Table 4. Firstly, it is possible to identify framework related solutions in which the most common application involves the adoption of multi-level structures, where each level can operate specific tasks (those including coordination, allocation, or perception). The development of such frameworks often addresses the integrated control problem. On the other hand, a single controller can be considered holistic when its design formulation is either multi-objective or multi-actuated. For the sake of completeness, the "miscellaneous" category refers to some specific application where the model or the sensing framework is considered holistic and will be further integrated in vehicle control systems. It should also be noted that the multi-objective property is very common when analyzing controllers; however, the conflicting terms, whose contribution must to be minimized, are usually limited to the vehicle system itself.

In the context of single controllers, it is necessary to mention the so-called Holistic Corner Control (HCC), originally introduced as the theoretical basis of the torque vectoring control [156], [157]. Its objective is to minimize the errors between target and actual forces and moments at vehicle's CG, ensuring that the desired path is followed while optimally distributing tire forces. Due to its nature, this framework can be easily employed in Four Wheel Driven (4WD) vehicles where the control of each wheel is realized through individual actuators. The output are generally the driving/braking forces at each corner and the HCC control is regarded as a nonlinear optimization strategy. However, the term holistic is sometimes ambiguously used, making it unclear whether it refers to an individual controller or the overall control structure. The HCC requires the evaluation of the actual forces at each corner [158] and a subsystem dedicated to identify their target values. This can be done by merging the driver's intention through a Driver Commands Interpreter (DCI) based on linear quadratic regulator theory [159]. Furthermore, the output need to be converted in actual wheel torques to be fed to the actuators through a dedicated layer. The optimization strategy generally involves three components:

- P1: error between the target and the actual values of longitudinal and lateral forces, and yaw moment: $E = [F_x - F_{x,d}, F_y - F_{y,d}, M_z - M_{z,d}]$;
- P2: control effort reflecting the actuator capabilities;
- P3: optimal distribution of tire forces satisfying the friction ellipse constraint.

Lastly, the definition of the weight matrices is often not static, as it can dynamically change the distribution of forces among the four corners.

Furthermore, some authors have proposed definitions of holistic vehicle control that either focus on the optimization of multiple objectives (such as mobility, stability, and safety) through the coordination of available control systems [160], or emphasize a comprehensive consideration of various influencing factors toward a single objective, such as stability [161]. From a methodological standpoint, Model Predictive Control (MPC) has been recognized as a powerful and widely adopted control method to handle dynamics constraints and design cost functions with multiple terms.

B. OUR DEFINITION OF HOLISTIC

Based on the considerations made in the previous chapters, the concept of holistic still remains ambiguous, demanding the authors to formulate a detailed definition on how future controllers should be conceptualized.

The design process should be structured on two levels (Fig. 10). The primary level aims to ensure that the

TABLE 4. Representative survey of "Holistic Vehicle Control" in literature.
Note that, particularly in historical works, the terms "MO"=multi-objective, "MA"=multi-actuated and "ML"=Multi-level often refer to integrated control of heterogeneous vehicle subsystems, whereas truly holistic control in the sense proposed in this manuscript corresponds to frameworks that explicitly include passenger, environment, or infrastructure as part of the control model and objectives ("V"=Vehicle; "P"=Passenger; "S"=Simulation; "E"=Experiments; "H"=Hardware in the Loop).

Holistic definition		Methodology	Application-Focus (Vehicle/passenger)	Validation	Ref.	Date
FRAMEWORK (ML)	MO MA	Control framework for AV: hierarchical structure	V- Platooning, longitudinal and lateral control	S, H	[37]	2023
	MO MA	Three levels MPC	V-MP for autonomous racing	S, E	[38]	2025
	MO	Hamiltonian-based trajectory planning+...	V-Connected AVs MP in urban scenarios	S	[39]	2024
	MO MA	Unified boundary value solver + MPC-like RT	V-High-speed MP of AVs on rough 3D terrain	E	[40]	2012
	MO MA	Learning based model + NMPC	V/P-AVs decision making, MP, and PT: safety, computational efficiency and P comfort	S	[41]	2023
	MO	Three levels	V-Safety AVs	E	[162]	2009
		ML	I-Management and control		[83]	1995
		Three levels (probabilistic driver model)	V-Safety + driver	S	[163]	2010
			V-Flexible integration of functionality from different suppliers control units		[82]	1999
SINGLE CONTROLLER	MO MA	MPC	V- Lat. control of AD functions when SBW failure	S	[164]	2025
	MO MA	Learning AMPC	V-Motion,stability and safety control coordination	S, E	[160]	2025
	MO MA	Multiple-model adaptive MPC	V-Four-Wheel Independent Drive (4WID) AVs	S	[165]	2025
	MO MA	Centralized MPC	V- PT (steering and braking)	S	[166]	2021
	MO MA	Active speed limiting control + TV (MPC)	V-Safety, stability and energy economy of three-axle electric bus DD and ARS	S	[158]	2025
	MO MA	Centralized MPC	V-PT and stability	S	[167]	2025
	MO MA	Three levels	V-4WD handling and stability+driver	E	[159]	2016
	MO MA	ML	V-PT and stability	S	[168]	2013
	MO MA	Hybrid learning MPC (ML)	V-Safety and performance	S, E	[161]	2023
MISCELLANEOUS	Model design	Experimental subjective data	P-ride comfort model		[169]	2024
	State estimation	Multi-modal model prediction + triggering mechanism	V-Safety monitoring system, uses available sensor data to find definition of "safety". Detect driver-initiated safety issues		[170]	2013
	MO index	Three levels (NN + fuzzy system + torque correction)	V-Stability through safety indicator	S, E	[171]	2025
	Driving scenarios		V-varying and validating AVs		[172]	2025
	Multi domain/integrated		V-4WD EV suspension design concept		[173]	2015

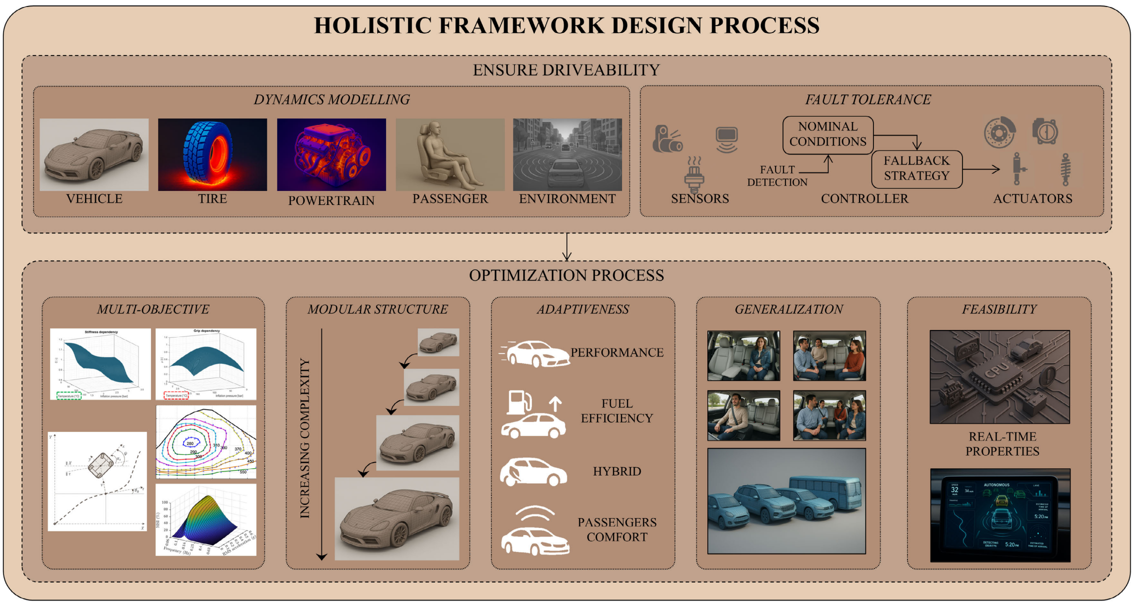

FIGURE 10. Holistic framework design process.

vehicle remains ''driveable'', reflecting the need to guarantee safety without compromising tire-road adhesion. Obviously, the knowledge of tires' thermal and wear state and road counter-face characteristics becomes crucial [174] in order to precisely define the boundaries of the safety domain. The additional layer refers to the optimization process that may consider comfort, efficiency, environmental impact. Those aspects can be seen as features or objectives that will be appropriately weighted within the control logic. The holistic property of such framework is reflected by the amount of features that are considered in the optimization process. A number of requirements should be stated to ensure an effective translation of theoretical considerations into practical application. Those are here summarized:

- Knowledge of system's dynamics and its subsystems, implying the capacity of modeling each feature through the related subsystem (e.g. for discomfort minimization the passengers dynamics should be known) within the controller's model. Consequently, the rising need of sensors and state sensing structures is here formalized;

- Multi-objective optimization, directly originating from the second level: this requirement is somehow already connected with research works on the topic of holistic vehicle control (see Fig. 4). Moreover, as the number of objectives grows the related actuation signals (control outputs) should grow accordingly, thus realizing multi-actuated systems;
- Modular structure: each part should be modular in the sense that, as the technologies evolve, the structure should allow the integration of more sophisticated models. This can be enabled by newer, even more performing hardware and software solutions leading to general openness of the framework which should guarantee interoperability property [10], [11];
- Adaptiveness: not only the sensing layer should provide the controller with precise states and parameters that must be representative of the system's operating conditions, but the controller should also be able to adapt to various scenarios. This refers to the possibility of differently weighting the features within the optimization phase (driving modes);
- Generalization: to ensure global spread in industrial applications and guarantee the effectiveness of the control framework, the structure should be generalizable to multiple vehicles and passengers (including the possibility of representing different occupants within the vehicle and their relative orientation);
- Fault tolerance: this property is closely related to the primary level, to ensure that the controller identifies the correct safe domain and stays within it, no matter the number of technical failures that can affect both sensors and actuators [175]. Redundancy and design strategies for fault tolerance represent the major keys to deal with these aspects [176], [177];
- Feasibility: real-time property and technical constraints of modern technology will be discussed in the next section. However, these represent keypoints toward actual real-world implementation of the above requirements.

In summary, our holistic definition clearly distinguishes from existing ''integrated,'' ''multi-objective,'' and ''multi-actuated'' approaches found in literature, with precise boundaries:

- Integrated control typically refers to the coordination of multiple vehicle subsystems (e.g., steering, braking, traction) to achieve improved vehicle performance, as demonstrated in electronic stability programs. However, integrated approaches remain fundamentally vehicle-centric and operate within predefined, static objective hierarchies;
- Multi-objective control encompasses simultaneous optimization of competing objectives such as safety, performance, and efficiency, yet these implementations often lack the adaptive weighting mechanisms and real-time parameter adjustment capabilities essential for passenger-centric functioning. Similarly, multi-actuated systems focus primarily on optimal force distribution among available actuators without considering the broader system-level interactions between heterogeneous subsystems.

In contrast, our holistic framework transcends these limitations through three distinguishing characteristics: (1) Cross-domain integration that bridges vehicle dynamics, passenger biomechanics, and environmental factors within a unified control architecture; (2) Adaptive multi-objective optimization with dynamic weighting mechanisms that respond to real-time passenger state, road conditions, and operational context; and (3) Modular scalability enabling seamless integration of additional subsystems (e.g., energy management, environment impact) without requiring fundamental architectural changes.

C. IS HOLISTIC FEASIBLE?

The following discussion aims at guiding the reader through the natural flow of a control architecture as each component both hardware and software contributes toward adding further layers of complexity, investigating the critical factors shaping the feasibility of the holistic framework, ultimately defining the complexity of its real-world bounds. Firstly, it is necessary to identify the target vehicle structure in which the framework should act to fulfill its objectives; although automation classes have been defined in the SAE J3016 [178], only few examples of production vehicles currently exploit L1-L2 features. Aside from the unique traits that characterize companies, AVs typically rely on common heterogeneous sensor suite. The description of each sensor along with their features/limitations has been summarized in Table 5.

It should be noted that the variety of sampling rates, processing requirements and latency profiles contribute toward introducing complexity and delays in the synchronization/sensor fusion phase. On the other hand, holistic controller must interface with multiple actuators, thus its operation should be hardly dependent on the subsystems' characteristics. In this context, the response time and control frequency are two crucial factors for the design of the control loop. A brief overview is proposed in Table 6.

Moreover, given that the proposed holistic framework emphasizes the management of increasingly computationally demanding tasks, it is essential to introduce constraints related to hardware limitation (Electronic Control Units ECUs). For automotive processes critical factors are: (i) Clock frequency (800-2000 MHz), (ii) Memory (80Kb-8Mb RAM, 1-32Mb Flash), (iii) the number of cores (1-3 up to 10) and, (iv) the temperature range ($-40\,°C$ up to $125\,°C$).

Lastly, all the mentioned entities (sensors, actuators, ECUs) need to interact through a common interface: to this purpose, communication protocols are introduced. From the network perspective, they are able to connect and share information between different entities; however, each technology has its own characteristics in terms of maximum bandwidth, load, delay, reliability, access mode, cost and application [55].

TABLE 5. Typical characteristics of automotive sensors used in AVs.

Sensor Type	Operating Frequency	Typical Range	Resolution / Data Rate / Sampling	Main Features and Notes
LiDAR	10–20 Hz (rotation), 905/1550 nm	60–300 m (typical: 100 m, up to 200–500 m)	Up to 250 Mbps (128 channels), <2 cm, 25–30 fps, 4–11 million points/s	High-precision 3D mapping
Radar	24–79 GHz (typically 76–77 GHz)	5–250 m	Centimeter to millimeter accuracy, 20–40 Hz (Doppler rate)	Velocity estimation and object tracking
Cameras	30–60 fps	Up to 250 m	1–8 MP, ≥ 30 fps, HDR, global shutter available	360° color vision
Ultrasonic Sensors	40–70 kHz	Up to 5 m (range may vary 0–30 m)	Low-resolution, binary or analog output	Low-speed maneuvers
GPS / IMU (6-DOF / 9-DOF)	–	Decimeter-level accuracy	Positioning accuracy <10 cm when fused	Vehicle localization and orientation

TABLE 6. Timing characteristics of automotive actuation systems.

System	Response Time	Control Frequency	Sources
Engine Control	100–200 ms [179] (e.g., EGR); 10–20 ms [180] (torque/throttle)	Up to 100ms (periodic task) [181], 40 Hz (25 ms) [182]	[179]–[182]
ABS / ESC	200–300 ms (complete cycle)	3–5 Hz [183]	[183]–[185]
EPS (Electric Power Steering)	300–500 ms (full loop) [186]	500 Hz [187], 800 Hz [188]	[186]–[188]
Transmission	100 ms to 2 s	10–100 Hz [81]	[81]

Having defined all the involved entities' requirements and their linkage, a deeper investigation should be made on the characteristics of the control-loop. Firstly, we will refer to the safety-critical hard real-time constraints [189] as they involve high-priority tasks which cannot be violated. They include engine, braking and steering control and are different from mission-critical (firm real-time) or comfort systems (soft real-time). Here, the latter do not include passenger comfort but can refer to infotainment or user-related tasks. Each category has its deadline and response time (dependent on the type of control entity). Within the control-loop, depending on the employed algorithm, the above requirements are translated into solver time constraints. Some general guidelines include solver utilization, which should be limited to 10-20 % of the sampling period [69] and, a schedule is assumed to be feasible if the total processor utilization does not exceed 60% [69]. Typical solvers include: simplified QP solvers (Active set, Interior Point [190], [191]); fixed complexity algorithms (fixed-point iteration [192]) and pre-solved parametric solutions [193]. The final layer is represented by the choice of the algorithm and the identification of its parameters. In this case, common sense suggests that the maximum allowable computational time for each step should be less than the sampling time. The most used strategies are here listed:

- PID/Fuzzy PID [194]
- LQR/LMI-LQR [195]
- Sliding mode/H_∞ [196]
- MPC/NMPC/Tube-MPC [197], [198], [199], [200]

while, regarding the MPC application, researchers have been widely investigating the limitations of such a powerful technology in real-world scenarios, with some quantitative information derived in:

- Number of states: **2** [201], 3 [202], 4 [203], 5 [199], 6 [204], 7 [197], **12** [198];
- Number of control inputs: **1** [199], [201], 2 [197], [202], [203], [204], **6** [198];
- Sampling time (ms): **10** [203], [205], 40 [204], 50 [202], 60 [197], **250** [201];
- Prediction horizon (steps): **5** [205], 20 [201], [202], [203], 25 [197], **30** [204].

In the context of the requirements and constraints presented, it becomes imperative to recognize that implementing a holistic controller in real-world AV scenarios necessitates a mentioned precise balance between ambition and feasibility. The holistic controller, by definition, aims to unify decision-making across perception, planning, and control subsystems, with the potential to optimize the vehicle's behavior in terms of safety, performance, passenger comfort, and energy consumption. However, this integration also significantly increases system complexity.

From a sensor point of view, the holistic controller must manage asynchronous data with various sampling rates and uncertainty profiles. Consequently, sensor fusion strategies must ensure temporal and spatial alignment, with resilience to latency and noise. This requirement alone poses a significant demand on pre-processing pipelines and real-time data association mechanisms.

From an actuation perspective, the performance of the controller is inherently constrained by the latency and bandwidth of the actuation systems. The broad range of response times—from tens of milliseconds (e.g., throttle control) to seconds (e.g., transmission systems)—necessitates the use of a holistic controller that is capable of comprehending the dynamics of individual subsystems and meticulously scheduling commands. Consequently, maintaining a uniform control frequency across all subsystems is often impractical, necessitating the adoption of *multi-rate control schemes* or hierarchical control architectures.

Since the capabilities of ECUs impose additional constraints on the deployment of the holistic controller, it is imperative to optimize the controller in terms of memory usage, computational time, and thermal footprint, with constraints becoming more pronounced when deploying computationally intensive control strategies, such as the Nonlinear Model Predictive Control (NMPC), especially when controlling multiple states and actuators simultaneously.

In the context of communication, network latency and reliability introduce additional variability to the control loop, necessitating the implementation of Time-Sensitive Networking (TSN) or event-triggered communication protocols to ensure deterministic performance—a prerequisite for safety-critical systems.

When evaluated in relation to the constraints imposed by the control algorithm, from the objective point of view it becomes evident that:

- **Sampling time:** the temporal parameters of sampling time for a holistic controller, particularly in scenarios that encompass high-level planning and low-level control, are typically maintained above 40–50 ms to ensure sufficient time for solver operations and data integration. This excludes extremely high-rate applications (e.g., EPS at 500–800 Hz) from being fully integrated into a single holistic loop unless offloaded to low-level controllers;
- **State and input dimensions:** it is imperative to ensure that the number of states and inputs remain manageable. As demonstrated by literature examples, the feasibility of real-time NMPC applications extends up to 12 states and 6 inputs. However, the majority of real-time implementations are constrained to fewer degrees of freedom to ensure real-time solvability;
- **Solver constraints:** it is essential to adhere to the constraints imposed by the solver, particularly the guideline that solver time should not exceed 20% of the sampling time. For instance, when a 50 ms sampling time is employed, the solver computation must complete within 10 ms. Attaining this objective can be particularly challenging for nonlinear or high-dimensional formulations.

Consequently, a holistic controller is particularly well-suited for mid-frequency control loops (e.g., 20–50 Hz), where the optimization of multiple subsystems can be achieved concurrently without compromising real-time constraints. High-frequency loops (e.g., ABS, EPS) should be maintained under decentralized or lower-level control strategies with dedicated processors.

In summary, while holistic control frameworks offer an elegant and theoretically optimal solution, their real-time implementation necessitates architectural decomposition, hardware-software co-design, and the adoption of modular, hierarchical control strategies. To address the real-time, safety, and computational requirements of modern AV systems, the holistic controller must distribute tasks and adjust prediction horizons, solver choices, and subsystem responsibilities.

V. FUTURE RESEARCH DIRECTIONS

Given the current overview and limitations, the objective of this section is to outline emerging research directions and to assess whether they can represent enabling factors toward the implementation and adoption of holistic controllers:

- Future vehicle design: The transition toward shared AVs is fundamentally reshaping both exterior and interior vehicle design. The removal of conventional driver and control interfaces has the potential to greatly influence the future design of interior automotive features, thereby expanding the range of possibilities beyond the constraints imposed by conventional forward-facing designs. Instead, flexible and reconfigurable seating layouts – such as face-to-face, U-shaped, and rotatable arrangements – are being actively explored to enhance passenger interaction, comfort, and functionality during transit [22], [206].
  Research has demonstrated that alternative seating arrangements can promote social interaction and enhance the travel experience, particularly in shared AVs [22], [80], [206]. For instance, face-to-face seating arrangements have been found to support postural comfort and a more communal travel environment, while reclining or rotatable seats can enable rest or personal space management during longer trips [206], [207]. These interior changes are supported by developments in sensor technologies, such as occupant detection and adaptive restraint systems, that ensure safety in non-traditional seating orientations [79], [208].
  Externally, AVs are moving toward more boxy, mono-volume shapes that prioritize interior space and modularity [22], [79], [209]. These designs facilitate a broad array of cabin functions, thereby transforming vehicles into mobile offices, social hubs, or restful environments, depending on the specific use case. Research has also emphasized the cultural and contextual variability in user preferences, suggesting that seat configuration should be adaptable not only to trip duration and activity but also to cultural expectations of privacy and interaction [52].
  In general, the design of vehicles is undergoing a transition from a driver-centric paradigm to a passenger-centered one. Dynamic and adaptive interior layouts are expected to play a central role in shaping future experiences related to mobility.
- Sensing background: The role of an accurate measurement and sensor fusion system has been widely recognized in AVs [49]. Nevertheless, the current level of automation is still limited due to various factors including guidelines, technology limitations and cost-driven constraints. Undoubtedly the current sensors' configuration will be refined through more cost-efficient solutions as stated in [23]. However, the formalized need of systems' dynamic knowledge can be assessed as the sensors could be extended to other non-vehicle systems (e.g passenger, tire).
- Sensing passengers: Recent research on passenger-oriented sensors relies heavily on physiological and biomedical monitoring to provide real-time, objective indicators. Key signals include EEG, ECG/HRV, and EDA/GSR, which have shown promise in identifying early signs of discomfort and outperforming traditional subjective assessments. EEG has been used to reveal changes in theta and alpha power during car sickness

episodes [101], as well as to develop real-time predictors using deep learning [102]. HR and HRV are gaining traction due to their usability and effectiveness, especially when combined with temperature or other physiological inputs [105]. While GSR and EDA are sometimes inconsistent at the individual level [115], they remain valuable when used in multimodal frameworks. Novel techniques, such as EGG and active seating systems with EMG sensing, also open new avenues for holistic controllers that simultaneously address comfort and motion sickness mitigation.
- Hardware definition: The increasing demand for real-time perception and control requires powerful and capable hardware [24]. Hybrid solutions are commonly preferred, integrating the simultaneous use of CPUs and GPUs; however the advances in models/algorithms highlight current hardware limitation. The key concerns include high efficiency and flexibility and a new generation of architectures is emerging. They will be characterized by heterogeneous structure with general-purpose CPUs and GPUs, tasks-specific accelerators (Processing-In-Memory PIM-based cores and Field-Programmable Gate Arrays FPGAs). A more concrete vision is proposed by the authors of [70] that adds to the previous properties traditional storage units (RAM, ROM, SD), communication interfaces (CANBUS, FlexRay, LIN, Bluetooth, Ethernet,..) and harvesting energy property. Moreover, they will support self- and remote-diagnostics, contributing toward failure/fault management.
- Machine Learning augmentation: Artificial Intelligence represents and undisputed trend in AVs design and control as stated in [47]. Originally the employment of machine learning techniques involved decision-making, localization and mapping [48] due to the necessity of perceiving the external surroundings. Indeed, the contribution toward adaptiveness property of future control systems is promising, not only as a feedback refinement that leverages external world information but also user preferences and behavior can be included. The success of these techniques relies on the quality of sensor data, fault management and high demanding computational resources. To this latter concept, there are still concerns to be addressed in terms of cost-performance ratio for commercial deployment.
- Cloud/edge computing: Most research contributions describe the future of embedded systems as distributed units with edge computing architectures [71]. Here, intelligent vehicles become connected as the limitations in computing resources represent a key obstacle in complex environments. Infrastructures are introduced as major players to limit the amount (and relative cost) of vehicle-related sensors, otherwise needed to increase the reliability and computing capability. Moreover, computational offloading has been recently introduced to extend single vehicle's computing capacity [210]. Vehicular Cloud (VC), Edge and Traditional Cloud (TC) are the three concepts that can be leveraged to define more complex structures (Vehicular Edge Computing VEC or Vehicular Fog Computing VFC) [211]. Some key objectives are: reducing response time, energy consumption, financial cost, overload and increasing system utility. To the current day there are, however, still open challenges that would require further investigation. Those include: signal attenuation, network congestion, fast speed of each node (vehicle), privacy, incentive for sharing resources and test environments [211].

Summarizing, future research must establish standardized validation framework to develop holistic framework demonstrating advantages over traditional integrated approaches. A minimal viable case study framework should compare the integrated and holistic controllers through a comprehensive assessment the following metrics: trajectory tracking accuracy, passenger comfort (via motion sickness metrics), energy efficiency, and computational performance across standardized driving scenarios including urban navigation, highway driving, and emergency maneuvers:
- Integrated controller: Traditional MPC with vehicle dynamics optimization, path tracking, and safety constraints, operating with fixed objective weightings and no passenger state consideration;
- Holistic controller: The same vehicle dynamics foundation augmented with: (1) Real-time passenger state estimation using simplified lumped-parameter human body model; (2) Motion sickness prediction incorporating MSDV and MSI metrics; (3) Adaptive multi-objective optimization with dynamic weighting based on passenger comfort state; (4) Cross-domain constraint coordination between vehicle performance and passenger comfort boundaries.

VI. CONCLUSION
Within the present article, the authors have investigated the urgent need to establish a novel framework to address the challenges posed by next-generation autonomous mobility. The discussion centers on the essential transition from integrated to holistic vehicle control design, emphasizing that this shift is not simply a matter of increasing model complexity or the number of objectives, but rather represents a true paradigmatic expansion, broadening both system boundaries and the depth of the models employed.

Holistic control intrinsically requires the fusion of heterogeneous domains (vehicle, passenger and environment) integrated through dedicated models, bidirectional information flow and unified optimization strategies, advancing beyond traditional vehicle-centric metrics of safety and performance and advocating instead for an orchestrated pursuit of broader objectives such as passenger comfort, adaptability, and societal acceptability.

To articulate this vision, the manuscript is structured around the modeling, sensing, and explicit inclusion of passenger state in the control objective function, based on both vehicle-side and human-centric sensing infrastructures. In this context, a detailed review presents the methodologies available for estimating passenger motion within the vehicle chassis, with particular attention to the trade-offs between model complexity, estimation accuracy, computational burden, and real-time feasibility for onboard systems.

The state-of-the-art in vehicle control architectures is then critically examined, spotlighting those approaches that potentially come closest to fulfilling the true definition of ''holistic'' within current literature. Finally, a clearly articulated vision for the development of future control frameworks is outlined, together with a discussion of the principal limitations that must be addressed for real-world implementation.

The conclusions of this work are here summarized:

- From a vehicle-related standpoint, the necessity of a complete (parameters/environment/states) sensing framework is stated. However, current research still lacks generalizable architectures that can operate effectively with commonly available and heterogeneous sensors. In addition, real-world feasibility entails several challenges which originate from the limited context of a simulation-only validation environment. These issues are further compounded by the need to manage increasingly accurate vehicle models alongside the technical constraints of the hardware infrastructure which has to handle the overall computational load.
- Common passenger state estimation methods including biometric sensors, human body modeling, transfer functions and motion sickness metrics (MSDV, MISC, MSI) present several limitations. Biometric sensors can be perceived as invasive and a single sensing method is often insufficient; indeed, multi-sensor fusion is a requirement for a complete assessment of passenger's state. Human body models, in particular the high-fidelity ones, are often computationally demanding, thus compromising the real-time deployability on onboard systems. Motion sickness metrics, still rely on subject-dependent tunable parameters, limiting their wide application. Future guidelines are not yet clearly established; however research should focus on: i) non-invasive and integrated sensing solutions; ii) computationally efficient models sustainable for real-time applications; iii) tailored estimators that are able to adapt to individual variability and susceptibility to motion sickness; and iv) standardized dataset and validation protocols to ensure comparability and reproducibility.
- Current literature on holistic vehicle control doesn't clearly define which guidelines/requisites should be met. Most common applications include multi-levels structures whose aim is to address the vehicle integrated control problem. Alternatively, the wording ''holistic'' refers to single controllers solutions where their design involves either multi-objective optimization or multi-actuated systems.
- The proposed definition of holistic framework can be articulated through two layers: drivability and optimization. While the former encompasses the necessity of guaranteeing safety and vehicle's controllability, the latter can include heterogeneous terms from multiple subsystems. Here, the importance of comfort, efficiency and environment is remarked. Therefore, specific requirements should arise. They include: knowledge/sensing of system's dynamics, optimization, modularity/generalization, adaptiveness and overall feasibility.
- The literature review continued, highlighting some limitations, and providing guidelines for the development of the next generation of AVs. In particular, in terms of:
  i) vehicle interior designs, currently constrained to a driver-centric layout and fixed seating position. In contrast, the transition toward passenger-centric designs, e.g., with reconfigurable interiors, may lead to enhanced comfort, social interactions, and trip functionality;
  ii) sensor system, still limited by cost, hardware computational constraints, and partial dynamic awareness. Future sensor networks will evolve to include additional systems, such as passenger, tires, etc., through multi-modal sensor fusion and cost-efficient solutions;
  iii) passenger state monitoring, often relying on subjective feedback or limited behavioral cues, leading to inconsistency at the individual level. Future approaches may aim to integrate biomedical signals, enabling real-time, objective assessment of passenger states;
  iv) hardware capabilities, struggling to meet the growing demands of real-time perception and control, due to limited computational power, energy efficiency, and integration of several components of diverse nature. In response, new generations of hardware are emerging, based on heterogeneous architectures combining general-purpose CPUs and GPUs, with task-specific accelerators (e.g. FPGAs and PIM-based cores);
  v) machine learning integration, which has shown the potential in AVs domain for decision-making, localization and environment perception tasks, although still constrained by issues related to data quality, computational demands and cost-performance ratios. Looking forward, machine learning is expected to significantly improve the adaptiveness of control strategies by incorporating both environmental cues and user-specific behaviors;
  vi) distributed computing, while vehicle connectivity increases, distributed systems may struggle to scale effectively, and face additional challenges such as network congestion and privacy concerns. A promising future direction involves the adoption of cloud/edge

computing enabling intelligent resource sharing and computational offloading.

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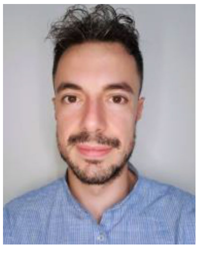

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