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LITERATURE REVIEW ON KINEMATIC PROPERTIES OF ROAD USERS FOR USE ON SAFETY-RELATED MODELS FOR AUTOMATED DRIVING SYSTEMS

Authored by

IEEE VT/ITS/AV Decision Making Working Group

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LITERATURE REVIEW ON KINEMATIC PROPERTIES OF ROAD USERS FOR USE ON SAFETY-RELATED MODELS FOR AUTOMATED DRIVING SYSTEMS

ABSTRACT

The task of driving is inherently risky. Human drivers rely on their experience from interacting with other road users to build assumptions of what constitutes a reasonably foreseeable behavior of the surrounding traffic in different situations, such as highway driving and urban driving. Together with explicit traffic rules, these assumptions help human drivers to navigate safely from point A to point B. With the development of Automated Driving Systems (ADS) and the introduction of ADS-equipped vehicles to public roads, the expectation of utilizing such technologies is that they will lead to a reduction of the inherent risk of driving. But in order to enable ADS' participation in traffic as well as to outperform human drivers in terms of safety, it is not enough to only rely on traffic rules adherence; ADS-equipped vehicles need to also consider assumptions about reasonably foreseeable behavior of other road users to be able to navigate safely and naturally on public roads. This document presents a review of relevant literature (e.g., standards, regulations, and scientific publications) that investigated kinematic behavior of road users. This review is intended to serve as a key contribution to the ADS research and industry communities, as well as to current standardization efforts, such as IEEE Std 2846, IEEE Standard for Assumptions in Safety-Related Models for Automated Driving Systems.

1. INTRODUCTION

Automated Driving Systems (ADS) are needed to help reduce vehicle crashes and improve road safety and traffic efficiency. But it is crucial for the industry to come to an agreement of "how safe is safe enough" when considering automated transportation. As recommended by the German Ethics Commission [1], for ADS technology to thrive on public roads there should be a positive risk balance compared to human driving performance.[1] While ADS technology can reduce human error in the transportation system, designing an ADS to account for the theoretical "worst-case" could result in an inefficient transportation system with overcautious, slow-moving traffic. Therefore, finding an appropriate risk balance is critical for the public adoption of ADS technology.

Human drivers today make use of their daily driving experiences when interacting with other road users in public roads. While doing this, drivers develop assumptions about reasonably foreseeable behaviors of the surrounding road users. These assumptions play an important role in the decision-making process of a responsible road user. For example, assumptions about the behavior of a leading vehicle might impact the consideration of an adopted following distance by a human driver. Assumptions about pedestrians near a crosswalk could affect the driver's behavior when approaching the crosswalk.

Assumptions about what are reasonably foreseeable behaviors of other road users can help an ADS to efficiently evaluate the vast space of possible situations it might encounter on the road, while maintaining sufficient safety considerations. When other road users perform within what is reasonably foreseeable to encounter, the ADS is expected to execute the driving task with an acceptable level of risk.

Recently published work on safety-related models for ADS, such as Responsibility Sensitive Safety (RSS) [2], Rulebooks [3], [4], Safety Force Field (SFF) [5], and Model Predictive Instantaneous Safety Metric (MPrISM) [6], among others, make use of assumptions to determine bounds (e.g., maxima or minima) of kinematic variables associated with surrounding road users. These bounds are used to determine an appropriate safety envelope around the vehicle, to constrain the ADS' operations, to rule acceptable vs. unacceptable planning actions, or to model the predicted behaviors of the surrounding traffic.

With such a rich range of implementations of assumptions in ADS safety-related models, the industry is starting to develop consensus on common definitions for such assumptions. This is the focus of IEEE Std 2846™-2022,

[1] The numbers in brackets correspond to those of the references in Section 7.

IEEE Standard for Assumptions in Safety-Related Models for Automated Driving Systems [7]. [2] IEEE Std 2846-2022 defines the minimum set of assumptions on the kinematic properties of road users to be considered by an ADS safety-related model. The standard also illustrates these assumptions by means of a road user taxonomy and sample common driving scenarios to be expected by an ADS. However, IEEE Std 2846 does not provide guidance on the values (or ranges of values) that these kinematic assumptions can take.

Therefore, the goal of this document is to present a summary of peer-reviewed scientific publications, related standard documents and active industry documents aiming to identify values for the kinematic properties of road users from data-driven studies. This publication is not intended to serve as a recommendation on reasonably foreseeable values for the assumptions to be used in safety-related models, as defined in IEEE Std 2846 [7]. The intent of this work is also not to define what constitutes a positive risk balance of ADS technology, nor to define "how safe is safe enough." Instead, this publication is intended to provide an overview of research-derived road user behaviors that could inform safety-related models in ADS. Furthermore, this publication aims to highlight existing gaps and limitations of the research to better focus efforts on understanding road user behaviors for safer ADS.

To this end, relevant published standards, active industry documents, and technical papers from corpus such as IEEE Xplore and SAE Mobilus were evaluated for their contributions to understanding kinematic properties of road users such as velocity, acceleration, or heading rate change. The selected publications were evaluated with respect to scientific rigor, applied methods, clarity, and applicability of the reported findings to values for road user behavior related to the driving task of an ADS, in the context of IEEE Std 2846. The result is a literature review compiling and summarizing reported values of kinematic properties of road users and a discussion of their applicability and use to inform assumptions about reasonably foreseeable behavior of road users. Note that this literature review is not intended to be an exhaustive evaluation of all research related to the kinematic properties of interest. Furthermore, organizations and ADS developers may have access to their own studies and data to supplement this document.

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2. ASSUMPTIONS IN SAFETY-RELATED MODELS FOR ADS

This section provides a high-level introduction of the assumptions about reasonably foreseeable behavior of road users (2.1) and the relevant driving scenarios (2.2) considered in IEEE Std 2846 [7].

2.1. ASSUMPTIONS ON KINEMATIC PROPERTIES OF ROAD USERS

Different types of road users exhibit different kinematic capabilities that may affect their behavior and interactions with an ADS. For example, pedestrians are able to perform larger directional changes than vehicles, but a pedestrian's maximum velocity is much lower than that of most motorized traffic participants. Therefore, within the scope of IEEE Std 2846, the assumptions about kinematic properties are based on the classification of different road user types, namely, Pedestrians, Bicyclists, Vehicles, and Other Vulnerable Road Users (VRUs), such as a person riding an electric scooter, or a person using a wheelchair. The Other VRUs category includes a wider spectrum of diverse road users' characteristics and capabilities, and thus, their kinematic properties may vary greatly, making it difficult to aggregate or summarize the information adequately. Therefore, a summary on kinematic properties for Other VRUs is not included in this literature review.

The kinematic properties of other road users include, among others, longitudinal and lateral velocities, accelerations, and decelerations,[3] and response time. The response time of a road user should be understood as the time it takes a road user to perceive a specific stimulus and start executing a response (e.g., braking, steering, etc.). See TABLE 1 for a complete list of the characteristics considered. Assumptions about these kinematic properties can take the form of bounding limits, such as reasonably foreseeable minimum and maximum boundaries (e.g., $\beta^{lon} \leq \beta^{lon}_{max}$), and their applicability depends on the driving scenario and the safety-relevant road users to be considered.

[3] The lateral deceleration of a road user, β^{lat}, can be understood as a lateral movement that results from an action that corrects or adjusts the lateral positioning of a road user, whereas a lateral acceleration, α^{lat}, can be understood as the lateral movement to perform a lateral maneuver under normal conditions (e.g., lane change).

TABLE 1 List of kinematic properties considered in IEEE Std 2846

Notation	Description
v^{lat}, v^{lon}	Lateral and longitudinal velocity of a road user
$\alpha^{lat}, \alpha^{lon}$	Lateral and longitudinal acceleration of a road user in its direction of travel
β^{lat}, β^{lon}	Lateral and longitudinal deceleration of a road user in its direction of travel
h	Heading angle (yaw) of a road user
h'	Heading angle rate of change (yaw rate) of a road user
λ	Lateral margin for small lateral fluctuation performed by road user moving in forward motion
ρ	Response time of a road user

2.2. DRIVING SCENARIOS TO BE CONSIDERED BY ADS-EQUIPPED VEHICLES

Driving scenarios define the spatial and temporal relationship between road users and include relevant characteristics of the scenery such as traffic signals and traffic rules governing the space [8]. An ADS-equipped vehicle navigating through the real world is expected to encounter a rich variety of driving scenarios, bounded by its Operational Design Domain (ODD) definition.

IEEE Std 2846 defines a non-exhaustive set of high-level driving scenarios in order to derive a minimum set of assumptions about the reasonably foreseeable behavior of other road users to be considered within the safety-related model of an ADS. These scenarios include common driving situations with longitudinal and lateral interactions between the ADS and other road users as well as interactions at intersections with and without the existence of occluded road users. Each scenario also introduces the minimum set of assumptions about reasonably foreseeable behavior, per road user category, to be considered by a safety-related model to avoid overly conservative driving behavior while maintaining the same level of safety operation.

During the temporal progression of a scenario, the ADS-equipped vehicle is expected to consider the defined assumptions and regularly update them, as the environment in which the ADS-equipped vehicle operates is dynamically evolving. Therefore, values of the assumptions for a road user might change as the ADS transitions from one scenario to another or when new road users become safety-relevant in the scene.

The scenarios in IEEE Std 2846 can be grouped into the following four high-level categories:

- **Longitudinal**: driving longitudinally in front and/or behind other road users

- **Lateral**: driving laterally adjacent to other road users
- **Intersection**: negotiating intersecting paths with other road users
- **Occlusion**: driving in areas where other road users could be temporarily occluded

The scenario denominations just listed will be used throughout the rest of the document for mapping reported kinematic properties found in the literature to the scenarios considered in IEEE Std 2846.

3. LITERATURE REVIEW

This section presents the review and summary of relevant studies and documents that provide empirical evidence of the driving behavior and kinematic properties of different road users. The studies are first contextualized by geographical location, experimental setup, road user type, and driving scenario. Following, summary tables containing kinematic values for each road user classification are presented and each reference is summarized to inform readers of how the resulting values were obtained.

3.1. CONTEXTUAL FACTORS TO CONSIDER FOR KINEMATIC PROPERTIES OF ROAD USERS

Driving behavior on public roads is in large part the result of a social construct; driving in Germany may be different than driving in China. What may be considered to be reasonably foreseeable behavior in one place could differ in another place. Therefore, there exist many contextual factors affecting the behavior of road users in public roads that are worth pointing out when studying kinematic properties of road users.

For instance, the geographic region may have an influence on road user behavior, due to the differences in innate social constructs, roadway infrastructure, and traffic rules, among others. Additionally, other factors such as weather-related environmental conditions, road surface conditions, traffic type, or other operational constraints, such as time of day, could impact the behavior of road users in public roads.

Therefore, in this section a summary of relevant contextual factors reported in the reviewed studies are presented. In particular, details about the following points are presented in TABLE 2.

- **Year:** Year(s) when the data collection took place. In case such information is missing, the year when the study was published is reported.
- **Country:** Country(ies) where the data collection took place. In case such information is missing,

the place where the study took place is reported.

- **Experimental setup:** Whether the study used Naturalistic Driving Data (NDD), data collected at a field test, or data collection from simulation.
- **Driving scenario:** Driving scenario from section 2.2, to which the study applies.
- **Roadway type:** Highway, urban, or campus.
- **Weather-related environmental conditions:** Weather-related information like precipitation and sky condition present in data.
- **Operational constraints:** Non-permissive constraints affecting the data collection, like time of day, or zones (school zone, university campus, etc.)
- **Sensors:** Sensor configuration used to capture the data. *On-board* is for sensors mounted on a road user (e.g., vehicle, or cyclist), and *off-board*, is for sensors not mounted on a road user (e.g., cameras mounted on roadway infrastructure or drones).
- **Data sample size:** The sample size of the data reported in the study.

An effort was made to harmonize the contextual factors of the studies' information with the ODD taxonomy presented by the SAE-ITC The Automated Vehicle Safety Consortium in AVSC Best Practice for Describing An Operational Design Domain: Conceptual Framework and Lexicon [9]. While the purpose of the taxonomy presented in AVSC Best Practice [9] aims at describing the ODD of an ADS, rather than describing the ODD of a particular dataset or study, it is important to make use of existing terminology, where applicable. For this purpose, the information under Operational Constraints column of TABLE 2 was completed based on the definition found in AVSC Best Practice [9] . Information under the Weather-Related Environmental Conditions column follows the definition based on AVSC Best Practice [9] and it also includes information about Road Surface Obscurants, such as wet or icy roads.

It is worth noting that the data sample sizes are shown for reference and details on how each data sample is defined is further described in 3.3, 3.4, and 3.5, where each reference is briefly explained. Since each study was designed differently, a consistent means of reporting the sample size was not possible. Moreover, none of the studies in TABLE 2 specifically addressed the occluded driving scenario considered in the standard.

TABLE 2 ODD-related information of reported kinematic properties

Ref	Year	Country	Experimental	Driving Scenario	Roadway Type	Weather-Related Environmental Conditions	Operational Constraints	Sensors	Data Sample Size
Pedestrians									
[10]	2011-2012	Canada	NDD	intersection	urban	sunny, dry road	afternoon peak hour	off-board	240 pedestrians
[11]	2016-2017	USA	NDD	intersection	urban	not reported	not reported	on-board	2,973 events
[12]	2012	USA	NDD	intersection, longitudinal	urban	not reported	not reported	on-board	201 veh-ped interactions
[13]	2010	USA	field test	longitudinal	N/A	N/A	N/A	off-board	8 adult subjects
[14]	1994, 1997	Sweden/ USA	NDD	longitudinal	not reported	not reported	not reported	on-board	460 participants
[15]	2016	China	NDD	intersection	urban	not reported	not reported	off-board	100 veh-ped interactions
[16], [17], [18]	2008	N/A	field test	N/A	N/A	N/A	N/A	N/A	N/A
Bicyclists									
[19]	2011-2012	USA	NDD	intersection, lateral	urban	mixed	mixed	on-board	1,000 veh-bic interactions
[20]	2020	USA	field test	longitudinal	N/A	dry road	N/A	on-board/off-board	16 events
[21]	2012	Germany	field test	longitudinal	N/A	not reported	N/A	off-board	30 subjects
[22]	2016	Germany	NDD	intersection	urban	sunny, dry road	morning peak hour	off-board	1,030 events
[23]	2008	United Kingdom	NDD	longitudinal, intersection, lateral	mixed	summer	not reported	on-board	16 participants, 100 min of data each
Vehicles									
[24]	2003	USA	field test	intersection	urban	clear sky, dry and wet road	not reported	on-board	245 subjects
[25]	2016	USA	simulation	longitudinal	mixed	N/A	N/A	on-board	48 drivers, 25 min per driver
[26]	2021	USA	NDD	intersection	mixed	not reported	not reported	on-board	41 adults, 2 routes of 12 km
[27], [28], [29]	2005-2006	USA	NDD	longitudinal, lateral	mixed	mixed	mixed	on-board	241 drivers, 2,000,000 miles
[30]	2006-2007	USA	NDD	longitudinal, lateral	mixed	mixed	mixed	on-board	108 drivers, 213,394 miles

Ref	Year	Country	Experimental	Driving Scenario	Roadway Type	Weather-Related Environmental Conditions	Operational Constraints	Sensors	Data Sample Size
[31], [32]	2019	Germany	NDD	intersection	urban	clear sky, dry road	not reported	off-board	6,500 veh. events at 4 intersections
[33]	2012	India	NDD	lateral	urban	sunny, dry road	morning peak hour	on-board	3 drivers, 20 events
[34]	2017	India	test field	intersection	urban	not reported	not reported	off-board	353 events
[35]	2012-2015	China	NDD	longitudinal	urban, highways	mixed	mixed	on-board	55 drivers, 161,055 km
[36]	2001, 2017	Japan	NDD, field test, simulation	longitudinal, lateral	highways	not reported	not reported	on-board/off-board	mixed sample sizes

3.2. SUMMARY OF KINEMATIC PROPERTIES OF ROAD USERS

A review and summary of the values for the kinematic properties of road users found in the literature is presented by road user classification in 3.3, 3.4, and 3.5. Note that values of kinematic properties reported in the analyzed studies only correspond to pedestrians, bicyclists, and light vehicles; information regarding other VRUs, or heavy trucks, were not found in the analyzed documents.

Special considerations had to be taken into account while consolidating a summary of the studies. Studies reported their findings in different units, so, in order to allow consistency in the presentation of kinematic values across studies, a units conversion to the metric system was applied. Acceleration values using Earth's gravitational acceleration units were converted, where 1 g = 9.81 m/s^2. Reported values were rounded to the closest decimal and standard deviation (SD) values are presented in the tables, where available. In addition, when possible, vector decomposition of the reported values was conducted to estimate the lateral and longitudinal components of the kinematic vectors.

3.3. KINEMATIC PROPERTIES OF PEDESTRIANS

Each reviewed document that investigated and/or analyzed pedestrian behavior is briefly introduced in this section. Reported values of kinematic properties of pedestrians from TABLE 1 are summarized in TABLE 3. Moreover, a brief explanation of each of the reviewed studies is presented below. This summary includes a report of the conditions under which the data collection/study was carried, and an explanation of the methodology used to derive road user behavior.

TABLE 3 Summary of kinematics values for pedestrians

Ref	v^{lon} [m/s]	v^{lat} [m/s]	α^{lon} [m/s²]	α^{lat} [m/s²]	β^{lon} [m/s²]	β^{lat} [m/s²]	ρ [s]	h [deg]	h' [deg/s]	λ [m]	Driving Scenario
[10]	4.6 (Max) 1.8 (Avg)	—	—	—	—	—	—	—	—	—	Intersection, jaywalker
[11]	1.5 (Avg)	—	—	—	—	—	—	—	—	—	Intersection, unsignalized, crosswalk
[12]	1.93 (Avg)	—	—	—	—	—	—	—	—	—	Intersection, crosswalk
[13]	(Walking) 1.8 (Max) (Jogging) 4.0 (Max)	—	—	—	(Walking) 4.8 (Max) (Jogging) 16.5 (Max)	—	(Walking) 0.68 (Avg) (Jogging) 0.65 (Avg)	—	—	—	Longitudinal, laboratory
[14]	(Walking) 1.5 [SD 0.2] (Avg) (Jogging) 2.5 [SD 0.3] (Avg Peak)	—	—	—	—	—	—	—	—	—	Longitudinal, laboratory
[15]	—	—	0.5 (Avg)	—	—	—	—	—	—	—	Intersection, crosswalk
[16], [17], [18] *	(Running) 12.4 (Max)	—	3.09 (Max)	—	—	—	—	—	—	—	Intersection, jaywalker

—: Not reported
Max: Report maximum value across all observations
Avg: Report average values across all observations
Avg Peak: Report average values across maximum values of individual observations
∗: World's 100 m dash champion record

Jakym, Atalla, and Kodsi [10] analyzed pedestrian kinematics adopted by jaywalkers when crossing a six-lane road (speed limit 60 km/h) in Canada. The authors included a comprehensive estimation of crossing speeds and evaluated the influence of the gap between pedestrians and approaching vehicles (in seconds) on pedestrian's speed. The authors collected behavioral information from more than 240 different pedestrians with 304 jaywalking instances. To control heterogeneity, the periods of data collections were conducted in good weather conditions (e.g., clear sky). The sample did not consider the crossing behaviors when a pedestrian stopped between lanes or in a diagonal direction. The results from this study supported average crossing speeds close to 1.8 m/s. This value decreased to 1.5 m/s when there was a large gap between the pedestrian and the vehicle and increased to 2 m/s when gaps were shorter, indicating a significant influence in the adopted speed when pedestrian is aware of the presence of an incoming vehicle. Finally, when looking at extreme values, the authors observed a maximum pedestrian speed of 4.6 m/s and minimum one of 1.0 m/s.

The study in “Evaluation of Automated Vehicles Encountering Pedestrians at Unsignalized Crossings” [11] observed probability density functions of pedestrian walking speeds under different conditions when interacting with a vehicle. The data collections involved 2973 passing events encountering pedestrians at unsignalized intersections. Pedestrians’ behavior was observed using Mobileye devices installed in university buses in Ann Arbor, Michigan. The estimated average values of pedestrian speed while crossing ranged between 1.1 m/s to 1.5 m/s depending on the clearance at the interaction with the vehicle using a multivariate Gaussian Mixture Model. This stochastic model aimed to provide a characterization of the interactions between buses and pedestrians at the observed signalized intersections. Additional conditions influencing the speed adopted by the pedestrians included the approaching speed of the vehicle and the time advantage (T_{Adv}). The time advantage being specified as the time between the first road user leaving the common spatial zone and the second one arriving, similar to definition of post-encroachment time.

“Pilot Study on Pedestrian Step Frequency in Naturalistic Driving Environment,” [12] evaluated pedestrian step frequency in a Naturalistic Driving Environment. The authors found that pedestrians tend to use higher step frequencies when crossing the road, compared to walking on the sidewalk, especially when the vehicle is moving towards the pedestrian or when pedestrians are crossing without the right of way. The authors found that pedestrians may increase their step frequency by about 14% when they do not have the right of way. In addition, when the vehicle has the right of way and is moving, an increase of step frequency of 18% was observed on average. Descriptive statistics for pedestrian crossing step frequencies in these difference scenarios are shown in TABLE 4. The calculation of walking speed using step frequency data is based on the v-f curves reported by Bertram and Ruina [37] and shown in TABLE 3.

TABLE 4 Pedestrian step frequency at crossing (steps/s)

Car Movement	Right-of-way	Mean	Standard Deviation
Vehicle Moving	Vehicle with Right-of-way	2.36	0.18
	Pedestrian with Right-of-way	2.07	0.16
Vehicle Stopped	Vehicle with Right-of-way	2.00	0.25
	Pedestrian with Right-of-way	1.93	0.15

Table reprinted with minor modification from “Pilot Study on Pedestrian Step Frequency in Naturalistic Driving Environment” in 2013 IEEE Intelligent Vehicles Symposium (IV), pp. 1215–1220 [12].

Additional studies provided measurements in more controlled environments rather than observations from naturalistic behavior. Wood, et al. [13] analyzed response times and deceleration values adopted by pedestrians in response to an (anticipated) auditory signal. This was a controlled experiment with a limited sample size of 8 subjects (7 males) with ages ranging from 18 to 50 years old. The authors observed a maximum longitudinal speed of pedestrians while walking of 1.8 m/s while the value increased to 4 m/s when they were jogging. In terms of the maximum adopted deceleration, the values were 4.8 m/s^2 (walking) and 16.5 m/s^2 (jogging). This study also looked at reaction times, measured from the provided signal to the first noticeable decrease in speed. The authors found average response times of 0.68 s when walking and 0.65 s when jogging. These values should be taken with caution since an auditory signal to stop was expected by the participants. This translates in shorter response times compared to someone reacting to an unexpected hazard.

SAE's standard J3116 [14] reviewed more comprehensive studies in line with specifications related to Active Safety used in Forward Looking Pedestrian Detection Systems. The standard cited studies involving more than 460 participants evaluating pedestrian gait behavior and speed while walking or jogging. The reported studies were conducted in Sweden and the USA. Based on the review, the maximum average adopted pedestrian speed was 2.5 m/s with an associated standard deviation of 0.3 m/s while jogging. The values reduced to a maximum comfortable pedestrian speed when walking to an average value of 1.5 m/s and standard deviation of 0.2 m/s.

Looking at safety-relevant interactions including near crashes, Tageldin and Sayed [15] observed pedestrians' gaits to allow extraction of conflict indicators. According to the authors, pedestrian gait served as superior kinematic signature and conflict indicator compared to traditional indicators such as Time to Collision or Post-encroachment time. The conditions from this study included high volumes of pedestrian and vehicles at one intersection in China. According to the authors, there was a low compliance of traffic laws with very short separation measures between different road users. Authors observed maximum change in step frequency adopted by pedestrians equal to 0.7 $steps/s^2$ in conflicting situations. Considering an average step length of 0.78 m, this translated into an acceleration of 0.5 m/s^2.

Finally, other studies that have evaluated pedestrians speed under emergency situations, such as evacuation scenarios [16], highlighted that the maximum acceleration of the world's 100 m dash champion was estimated as 3.09 m/s^2. This value was calculated based on Rhett Allain's approach on the maximum acceleration in the 100 m dash [17]. As per the top speed achieved by the world's 100 m dash champion record, the value reported topped a 12.4 m/s (Utathya [18]).

3.4. KINEMATIC PROPERTIES OF BICYCLISTS

Each reviewed document is briefly introduced, with mention of relevant characteristics and contextual information when deriving values for the kinematic properties of bicyclists from TABLE 1. Values found in the literature for bicycles are summarized in TABLE 5 and further explained in the text that follows.

TABLE 5 Summary of kinematics values for bicyclists

Ref	v^{lon} [m/s]	v^{lat} [m/s]	α^{lon} [m/s²]	α^{lat} [m/s²]	β^{lon} [m/s²]	β^{lat} [m/s²]	ρ [s]	h [deg]	h' [deg/s]	λ [m]	Driving Scenario
[19]	6.9 (Along-75th Pct) 6.3 (Cross-75th Pct) 4.0 (Cross Stop-75th Pct)	—	1.4 (Avg)	—	—	—	—	—	—	—	Intersection, Lateral
[20]	—	—	—	—	6.9 (Avg)	—	—	—	—	—	Longitudinal
[21]	4.3 [SD 0.6] (Avg)	—	0.6 (Avg)	—	5.5 (Max)	—	—	—	—	—	Longitudinal
[22]	6.02 [SD 1.29] (Avg Peak) 5.23 [SD 1.25] (Cross-Avg Peak)	—	0.8 (Stop-Avg) 0.2 (Moving-Avg)	—	0.6 (Avg)	—	—	—	—	—	Intersection
[23]	11.0 (Max) 6.0 [SD 1.7] (Avg)	—	0.7 (Max) 0.3 [SD 0.1] (Avg)	—	—	—	—	—	—	—	Longitudinal

—: Not reported
Max: Report maximum value across all observations
Avg: Report average values across all observations
Avg Peak: Report average values across maximum values of individual observations

In terms of naturalistic studies from bicyclists, SAE Standard J3157 [19] provides a comprehensive overview of a study conducted in the metropolitan area of Indianapolis from 2011 to 2012 (Fu, et al. [38]). This study analyzed tracking information from a total of 1000 trajectories. These trajectories were utilized to provide specifications/requirements for target identification of bicyclists using forward-looking bicycle detection systems. The study looked at different adopted bicycles speeds when traveling parallel to the traffic (i.e., lateral driving scenario) or in crossing areas (i.e., intersection driving scenario). Based on the findings, the average bicyclist acceleration observed was 1.4 m/s². When looking at the distributions from the speeds, the presented values of TABLE 6 summarize the findings for the average, 25th and 75th percentiles of adopted speeds across scenarios.

TABLE 6 Speed values from SAE J3157 [19]

Scenario	Longitudinal Speed Assumptions [m/s]		
	Average	25th Percentile	75th Percentile
Traveling Parallel to Traffic	5.6	4.1	6.9
Crossing Traffic	5.2	4.0	6.3
Crossing Traffic from Stationary Position	3.5	2.8	4.0

Famiglietti, Nguyen, Fatzinger, and Landerville [20] performed field tests consisting of a bicyclist executing several brake-to-stop tests. The tests were executed using different bicycle types, namely, hybrid bikes, beach cruisers, BMX bikes, road bikes and single speed bikes. For each test, the rider accelerated until reaching a test speed, which ranged between 5 m/s and 10 m/s, and upon entering the braking area, applied maximum braking force. The resulting average deceleration rates across all bikes models ranged between 4.0 m/s^2 and 6.9 m/s^2 for front and rear brake application and 2.5 m/s^2 and 3.6 m/s^2 for rear-only brake application.

The work in “Basic driving dynamics of cyclists” [21] conducted a closed course experimental set up to guide estimation of a Necessary Deceleration Model (NDM) characterizing car-following behavior of bicycles. The experiment looked at interactions between bicycles driving longitudinally behind one another, exclusively. Based on the findings from the authors, assumptions derived from the kinematics of bicycles strongly depend on whether the bicycle is accelerating or traveling at the cruising speed. This study supported an average and desired longitudinal speed of bicycles equal to 4.3 m/s (SD 0.6). On average, it took 20 m to 25 m to accelerate to the desired speed and the duration of the acceleration phase was about 7 s. This translates to average accelerations of 0.6 m/s^2. Moreover, the results support minimum standing distance between bicycles as 0.2 m, headway in car following as 0.7 seconds, and maximum adopted deceleration of 5.5 m/s^2.

The study done by Twaddle and Grigoropoulos [22] also documented a comprehensive characterization of adopted kinematics by bicyclists in diverse conditions in Munich, Germany. The authors processed 1,030 trajectories at four intersections near to downtown Munich to characterize acceleration and deceleration profiles. The study looked at the behavior of bicyclists in three different states: while bicyclists accelerated from a stop position, decelerated to a stop, and while in motion fluctuating around a desired traveling speed. The average values of acceleration from a stopped position indicated rates around 0.8 m/s^2. This value reduced to 0.2 m/s^2 when fluctuating around the desired speed. The values for deceleration showed average values close to 0.6 m/s^2. The authors also reported the maximum average speeds close to 6.0 m/s (SD 1.3). The values when looking at crossing signalized intersections were slightly lower with an average peak crossing speed of 5.2 m/s (SD 1.3).

Other reviewed studies looked at behavior in closed course or instrumented bicycles. Parkin and Rotheram [23] analyzed adopted speeds from a cohort of bicycles using GPS. The sample includes 16 volunteers (4 female, 12 males) usual cycling commuters from the city of Leeds in UK. The study evaluated maximum adopted speeds in road gradients ranging from –8.4% to 9.3%. Based on the results, the maximum adopted speed across all experiments was 11.0 m/s while the maximum observed acceleration was 0.7 m/s^2. The mean values for speed were 6.0 m/s (SD 1.7). The average values for acceleration were 0.3 m/s^2 (SD 0.1).

3.5. KINEMATIC PROPERTIES OF VEHICLES

Each reviewed document is briefly introduced with mention of relevant contextual information when deriving the values for kinematic properties of vehicles described in TABLE 1. Values found in the literature for vehicles' kinematics are summarized in TABLE 7 and a general overview of the studies is presented below.

TABLE 7 Summary of kinematics values for vehicles

Ref	v^{lon} [m/s]	v^{lat} [m/s]	α^{lon} [m/s²]	α^{lat} [m/s²]	β^{lon} [m/s²]	β^{lat} [m/s²]	ρ [s]	h [deg]	h' [deg/s]	λ [m]	Driving Scenario
[24]	—	—	—	Dry: 2.5 [SD 1.7] Wet: 2.2 [SD 1.0] (Avg Peak)	Dry: 7.0 [SD 2.3] Wet: 4.4 [SD 1.0] (Avg Peak)	—	Dry: 1.17 [SD 0.31] Wet: 1.09 [SD 0.28] (Avg)	—	—	—	Intersection
[25]	—	—	—	—	—	—	1.3 (Median)	—	—	—	Longitudinal
[26]	—	—	1.5 [SD 0.4] (Avg)	—	1.6 [SD 0.6] (Avg)	—	—	—	23.4 [SD 4.5] (Avg)	—	Intersection
[27]	—	—	—	—	Follower vehicle: 5.4 (90th Pct Avg) 9.3 (90th Pct Max)	—	—	—	—	—	Longitudinal
[28]	—	—	Follower vehicle: 3.8 (Max)	5.8 (Max)	Follower vehicle: 5.8 (Max)	—	—	—	—	—	Longitudinal, Lateral
[29]	—	—	—	—	Follower vehicle: Near-crash: 7.1 (Peak Median) 1.8 (Median) Incidents:	—	Follower vehicle: Near-crash: 1.3 (Median) Incident: 1.0 (Median)	—	—	—	Longitudinal

Ref	v^{lon} [m/s]	v^{lat} [m/s]	α^{lon} [m/s²]	α^{lat} [m/s²]	β^{lon} [m/s²]	β^{lat} [m/s²]	ρ [s]	h [deg]	h' [deg/s]	λ [m]	Driving Scenario
					5.1 (Peak Median) 1.5 (Median)						
[30]	—	1.6 (Avg Peak)	—	0.9 (Avg Peak)	1.5 (Avg Peak)	—	—	—	—	—	Longitudinal, Lateral
[31], [32]	—	—	2.3 (99th Pct)	2.8 (99th Pct)	2.7 (99th Pct)	—	—	—	—	—	Intersection
[33]	—	—	—	1.5 (Max)	—	—	—	—	2 (Max)	—	Lateral
[34]	—	—	Petrol vehicles: 2.8 (Max) 0.7 (Avg) Diesel vehicles: 2.0 (Max) 0.5 (Avg)	—	Petrol vehicles: 4.3 (Max) 2.6 (Avg) Diesel vehicles: 4.5 (Max) 3.7 (Avg)	—	—	—	—	—	Intersection
[35]	—	—	—	—	Lead vehicle: 6.5 Follower vehicle: 6.0 (Avg Peak)	—	—	—	—	—	Longitudinal
[36]	—	—	—	1.8 (3σ)	Follower vehicle: 7.6 (Peak Median)	—	0.8 (Lateral) (Avg)	—	—	0.375 (Median)	Longitudinal, Lateral

—: Value not reported in the study
Max: Report maximum value across all observations
Avg: Report average values across all observations
Avg Peak: Report average values across peak values of individual observations
Median: Report median value across all observations
Peak Median: Report median value across peak values of individual observations
3σ: Report value 3σ from the mean

The National Highway Traffic Safety Administration (NHTSA) [24] explored differences between vehicles equipped with conventional and ABS brakes, investigating a rationale for ABS-equipped vehicles having a higher chance of road-departure field incidents. Authors reported the mean initial response times and the magnitude of braking and steering actions of human drivers in response to an intersection incursion scenario, with the incursion vehicle on the right, for both dry and wet pavement. In the case of initial response time, the mean values found were 1.2 s (SD 0.3) for dry pavement and 1.1 s (SD 0.3) for wet pavement. For longitudinal deceleration, the mean peak deceleration values reported were 7.0 m/s^2 (SD 2.3) in dry pavement and 4.4 m/s^2 (SD 1.0) for wet pavement. When broken down by brake system, across both pavement conditions, the mean peak deceleration was found to be 6.5 m/s^2 (SD 2.4) for subjects with ABS and 6.4 m/s^2 (SD 2.4) for subjects with conventional brakes. For lateral acceleration, the mean peak lateral accelerations values reported were 2.5 m/s^2 (SD 1.7) and 2.2 m/s^2 (SD 1.0) for dry and wet pavement, respectively. All tests were done on a test track in a controlled environment.

In Blommer, et al. [25], a study of driver brake vs. steering was done in order to measure a non-distracted driver's response to a sudden forward collision event. The study was done in a VIRtual Test Track Experiment (VIRTTEX) simulator facility with 48 volunteers between the ages of 23 and 50. Three different configurations on the simulated vehicle were investigated: automated vehicle with full collision avoidance control, automated vehicle without collision avoidance control, and manual mode. The median response times to sudden events were reported to be 1.3 s, 1.4 s, and 1.5 s for manual, automated without collision avoidance, and automated with collision avoidance modes respectively.

The work presented in the SAE Technical Paper [26] studied naturalistic driving behavior in urban and highway scenes in Los Angeles, California, by performing right turn maneuvers at stoplight-controlled and partially signalized intersections using instrumented test vehicles. Mean values for longitudinal deceleration rates, acceleration rates, and angular velocities were extracted from the data after applying data smoothing algorithms to reduce high-frequency noise. Note that there was no obvious trend in the data suggesting that right-turning drivers altered their behavior depending on the phase of the traffic light at the intersections analyzed.

Several studies evaluated the 100-Car Naturalistic Driving data [39] by filtering the dataset and categorizing the data samples based on the particular focus of each study. For example, another work done by the National Highway Traffic Safety Administration [27] explored the use of real crash data collected in The 100-Car Naturalistic Driving Study, Phase II-Results of the 100-Car Field Experiment [39] to investigate the potential of collision avoidance systems in avoiding rear-end crashes. Various driver behavior and performance measures were also collected during the events, such as driver braking behavior. The mean deceleration achieved by drivers in the data used in this study appeared to be much lower than the maximum deceleration. The reported 90th percentile mean deceleration was 5.4 m/s^2, while the 90th percentile maximum deceleration was 9.3 m/s^2.

The work in Klauer, et al. [28] compared behavior of drivers with low and high rates of crashes and near crashes using the data from the 100-Car Naturalistic Driving Study, Phase II-Results of the 100-Car Field Experiment [39]. This study classified drivers into *safe*, *moderately safe*, and *unsafe* based on occurrence of crashes and near-crashes per million miles driven, with unsafe drivers having more than 900 crashes and near-crashes per million miles driven. The authors analyzed the frequency at which each driver category engaged in lateral and longitudinal accelerations, longitudinal decelerations, and swerving maneuvers of 20,000 six-second epochs randomly selected from the dataset. The entire duration of the selected trips was used as a continuous data to assess the frequency of acceleration and deceleration events. For acceleration and deceleration analysis, the frequency of the occurrences was calculated using 0.98 m/s^2 (i.e., 0.1g) bins. The authors reported that drivers in all three categories exhibited peak lateral accelerations within the ranges of 2.9 m/s^2 and 4.8 m/s^2 more frequently compared to any other ranges of values during swerving maneuvers but pointed out that unsafe drivers exhibited lateral accelerations between 2.9 m/s^2 and 5.8 m/s^2 significantly more frequently than the other driver categories. Lateral accelerations greater than 5.8 m/s^2 were very infrequent in the analyzed data. In the case of longitudinal accelerations, 88% of drivers exhibited accelerations in the 2.9–3.8 m/s^2 range, but authors pointed out that unsafe drivers engaged in higher accelerations more frequently than the other driver categories. For deceleration, the reported deceleration rate of most drivers was within the 2.9 m/s^2 and 5.8 m/s^2 range. The authors noted that drivers do not tend to brake harder than 5.8 m/s^2 very frequently, even in emergency situations (i.e., crashes, near-crashes).

Similarly, analyses of the 100-Car Naturalistic Driving study [39] on rear-end crashes and near crashes for rear-signaling countermeasure were reported in a work by the U.S Department of Transportation (USDOT) [29]. This report analyzed different aspects of driver behavior, such as response time and deceleration rate of drivers in car-following situations, among others. Events were classified into crashes, near crashes, and incidents. Near crashes are events in which a deceleration was harder than 5.1 m/s^2 or where a lateral acceleration greater than 3.9 m/s^2 was applied. Incidents, on the other hand, are events in which a crash avoidance response is applied (i.e., any control input that falls outside of the 99-percent of confidence of the control input but is less severe than a near-crash response). A total of 2873 events were analyzed, with 160 near-crashes and 2713 incidents. Regarding the response time of follower drivers after a lead vehicle started decelerating, the median brake-response time was 1.3 s for near-crash events, and 1.0 s for incidents. The authors noted that drivers in incidents had faster brake response times than drivers in near crashes. In the case of deceleration of a follower driver, median peak deceleration was 7.2 m/s^2 for near crashes and 5.1 m/s^2 for incidents. In contrast, the median values for the averaged deceleration rates during the braking event was found to be 1.8 m/s^2 for near-crashes, and 1.5 m/s^2 s for incidents.

In a report issued by the National Highway Traffic Safety Administration [30], integrated vehicle-based safety systems (IVBSS), such as forward collision warning and lane departure warning, were evaluated in order to gain detailed understanding of the benefits of such systems. The evaluation was conducted by analyzing naturalistic driving data collected from a field operational test with 108 subjects with vehicles equipped with IVBSS. A portion of the tests included the IVBSS passively monitoring the driving behavior without issuing a warning to the driver, and another portion of the tests included the IVBSS with alerts enabled. In alert episodes with valid hazards, driver response was compared between the period where drivers did not receive alerts and the period where they did. Out of the tests with the alerts disabled, drivers reported an average peak deceleration of 1.5 m/s^2 in forward collision conflicts. For the lateral conflicts, the drivers exhibited an average peak acceleration of 0.7 m/s^2 for lane departure conflicts and 0.9 m/s^2 for lane change conflicts, with an average peak lateral speed of 0.8 m/s and 1.6 m/s respectively.

Pasch, Oboril, Gassmann, and Scholl [31] analyzed a naturalistic driving dataset that contains trajectories of more than 11500 road users including vehicles, bicyclists, and pedestrians at intersections in Germany captured with a drone (Bock, et al. [32]). The 99th percentile values on longitudinal and lateral acceleration and longitudinal deceleration were extracted. The 99th percentile values found were 2.3 m/s^2, 2.8 m/s^2, and 2.7 m/s^2, for longitudinal and lateral acceleration and longitudinal deceleration, respectively.

The work of Mahapatra and Maurya [33] studied lateral and longitudinal behavior of vehicles in mixed traffic conditions on Indian highways on straight roads without defined lanes. The authors looked at lateral acceleration, and speed values, the relationship between the vehicle longitudinal speeds with the lateral characteristics and the relationship between lateral acceleration and heading angle with longitudinal speed. The traffic data is from a 3 km stretch of straight road in India, in dry weather. The maximum values for lateral acceleration and heading angle rate of change were reported to be 1.5 m/s^2 and 2 deg/s, respectively.

"Acceleration-Deceleration Behaviour of Various Vehicle Types" [34] studied the acceleration and deceleration behaviors of different vehicle types in Indian roads due to the heterogeneity of Indian traffic. The experiment took place at a controlled test site, where all drivers were asked to speed up their vehicles from stop condition to achieve their desired speed as early as possible. After cruising at desired speed for some time, drivers were asked to decelerate to stop condition in shortest possible time to simulate lead vehicle behavior at signalized intersection. Different vehicle types, such as diesel and petrol cars, that were privately owned by the volunteers were part of the experiment. For the acceleration behavior, maximum longitudinal acceleration rate and mean longitudinal acceleration rate at the highest speed (between 10 m/s and 25 m/s) for each of the different vehicle types were reported as follows: 2.0 m/s^2 and 0.5 m/s^2 for diesel cars, and 2.9 m/s^2 and 0.70 m/s^2 for petrol cars. The authors noted that the maximum and mean longitudinal acceleration rates were higher at higher maximum speeds. In the case of deceleration rates, maximum longitudinal deceleration rate and mean longitudinal deceleration rates of different vehicle types at the highest speed were reported as follows: 4.5 m/s^2 and 3.7 m/s^2 for diesel cars, and 4.3 m/s^2 and 2.6 m/s^2 for petrol cars.

The work done by Xu, Wang, Wu, Hassanin, and Chai [35] calibrated the RSS (Shalev-Shwartz, Shammah, and Shashua [2]) safety model's parameters for car-following situations using Naturalistic Driving Data collected for more than three years in Shanghai, China on roads including freeways, and urban scenes with different weather conditions. Authors identified 223 safety critical events from the dataset used to calibrate the parameters of the safety model. Among the identified events, the authors reported a mean peak longitudinal deceleration of 6.5 m/s^2 and 6.0 m/s^2 for the lead vehicle and the follower vehicle, respectively. Authors also reported vehicle's mean longitudinal speed of vehicles, but there is no correlation reported between the speed values and speed limit of the roads. In this work, there is no characterization of the values reported based on weather or road conditions.

In "Competent and Careful Human Driver Performance Model" [36], Japanese experts presented relevant aspects of a "Careful and Competent Driver" to the United Nations Economic Commission for Europe (UNECE), Functional Requirements for Automated and Autonomous Vehicles (FRAV) group. This presentation is a compilation of studies and experiments of human drivers in several driving scenarios that characterize risk perception time of human drivers in cut-in situations, as well as maximum lateral acceleration, risk perceived boundary, and maximum deceleration in car-following scenarios. For risk perception time, experiments on a test field were carried out with experienced drivers and the average time to react to a cut-in was defined as 0.8 s. For maximum lateral acceleration, a three standard deviation value was defined as 1.8 m/s^2 out of 911 NDD cases. In the case of risk perceived boundaries, the 50th percentile value of a dataset containing 5244 evaluated instances was extracted. This value resulted to be 0.75 m (0.375 m for each side) and represents the lateral distance in which a vehicle is still considered to be wandering within its own lane and not performing a lateral maneuver (i.e., cut-in). For maximum longitudinal deceleration force applied by drivers, a study comparing 245 trained drivers and 36 regular drivers found that the first group applied a median longitudinal deceleration greater than the second group, with values of 7.6 m/s^2 versus 6.7 m/s^2, respectively. Throughout these experiments, there is no characterization of the weather and the road condition.

4. DISCUSSION ON REASONABLY FORESEEABLE BEHAVIOR OF ROAD USERS

Assumptions about what is a reasonably foreseeable behavior of other road users are at the core of IEEE Std 2846; therefore, a discussion of the reported behavior of road users from documents reviewed in Section 3 is presented next.

As different studies reviewed reported their findings differently (e.g., maximum, average peak, average, median), it is important to put the values from TABLE 3, TABLE 5, and TABLE 7 in context and to discuss the similarities and discrepancies between the numbers found.

4.1. DISCUSSION ON PEDESTRIAN KINEMATICS

The studies looking at pedestrian kinematics showed consistent values across the cited papers. A distinction between pedestrians walking or jogging was necessary to define specific characteristics from humans in these two distinct behaviors. When looking at jogging, the maximum longitudinal velocity of pedestrians ranges between 4 m/s to 5 m/s as supported by Jakym, Atalla, and Kodsi [10] and Wood et al. [13]. There are some discrepancies in the values from the study in SAE J3116 [14] considering a greater sample size and a more difficult distinction between these two behaviors in a large-scale analysis. However, assuming the maximum observed value as at least three standard deviations from the reported mean, the results support a maximum longitudinal velocity value of 3.2 m/s, an estimate closer to the reported range by the other authors. There is more consistency of pedestrian kinematics when walking with an average longitudinal velocity of 1.5 m/s, as supported by [10], [14], [13], [11]. When estimating the value of speed increased by three standard deviations from the mean while walking, the value increases to 2.0 m/s. A more rigorous analysis of the contextual situation of pedestrians while crossing is necessary to account for the significant differences reported in crosswalk vs. jaywalk crossing. Average crossing speeds were consistently reported around the 2.0 m/s value. However, the presence or absence of incoming vehicles could radically affect kinematic values like velocity and acceleration. As reported in Jakym, Atalla, and Kodsi [10], jaywalkers demonstrated average speeds of 2.4 m/s at the most critical negotiating gap of 5 seconds with incoming vehicles. “Pilot Study on Pedestrian Step Frequency in Naturalistic Driving Environment” [12] reports an increase of 18% in the stepping rate of pedestrians comparing reactions to stopped vs. moving incoming vehicles at signaled intersections, which reflect a comparable response to criticality. When looking at the values for acceleration of pedestrians, the results depicted average accelerations close to 0.5 m/s^2. It is worth pointing out that the reported acceleration from the fastest human being recorded to date (Allain [17]) reached a value of 3.0 m/s^2 during an Olympic competition, being this an extreme case and a point of comparison when defining what is to be considered reasonably foreseeable behavior of pedestrians.

When looking at deceleration adopted by humans, there is a strong discrepancy when walking or jogging with maximum deceleration rates reaching values up to 16.5 m/s^2 (Wood, et al. [13]).

The study in Wood, et al. [13] reported response times from hearing signals close to 0.68 s when a pedestrian is walking and 0.65 s while jogging. These values could be considered as a lower bound since participants were expecting hearing cues from the controlled experiment. A revision of more studies is needed to contrast these results as human reaction in non-controlled environments with higher complexity is expected to be longer.

4.2. DISCUSSION ON BICYCLIST KINEMATICS

The studies evaluating the kinematic behavior of bicyclists depicted longitudinal velocities depending on the type of the maneuver and interaction with other road users. The reported values for bicyclists' longitudinal velocity are lower when crossing traffic. In general, average peak values of longitudinal velocity and high percentiles are in the region between 6–7 m/s. However, maximum values can reach up to 11.0 m/s (Parkin and Rotheram [23]). This also aligns with a maximum longitudinal speed value of 9.9 m/s, calculated as three standard deviations from the average of maximum value reported in Parkin and Rotheram [23].

On the other hand, there is some heterogeneity in the values reported for the adopted longitudinal accelerations by bicyclists. A potential explanation for the discrepancy is the difference in behaviors of bicyclists when accelerating from a stopped position and when bicyclists remain traveling at desired speeds. The cited papers only reported average values of acceleration from a stopped position ranging from 0.8 m/s^2 up to 1.4 m/s^2. Acceleration values when traveling at desired speed were around 0.2 m/s^2.

When looking at the longitudinal deceleration, the maximum observed values were between 5.5 m/s^2 to 6.9 m/s^2 on average, over a set of field tests. Other studies that analyzed NDD found average deceleration values close to 0.6 m/s^2 on average. These results highlight the differences between reported values coming from field tests vs. NDD data.

4.3. DISCUSSION ON VEHICLE KINEMATICS

From the reviewed studies that analyzed vehicle behavior, when looking at longitudinal deceleration values reported, most documents referred to a peak value ranging between 4.4–7.6 m/s^2, as supported by [24], [28], [34], [35], [36]. The reviewed documents included naturalistic driving studies, as well as experiments on a test track. The contextual details provided in the papers are generally not enough to evaluate value differences across naturalistic or controlled settings. However, the work by the NHTSA [24], identified values in different road conditions, highlighting how human braking behavior changes on wet pavement compared to dry pavement. When looking at values across all pavement conditions (i.e., dry, and wet), the NHTSA document [24] reported that the mean peak deceleration achieved for subjects with conventional brakes was 6.3 m/s^2 (SD 2.4 m/s^2, max 10.5 m/s^2, min 0.5 m/s^2). The maximum reported value of 10.5 m/s^2 from NHTSA [24] goes in line with what the authors of NHTSA [27] reported to be the 90th percentile peak deceleration of 9.3 m/s^2. The authors of NHTSA technical report [27] pointed out that in the near crash and crash events analyzed, a collision could have been avoided by braking with at least 4.9 m/s^2 as late as 2.0 s prior to the predicted (or actual) point of impact even though maximum braking rates reported reached a value close to 9.81 m/s^2 (i.e., 1 g).

It is worth pointing out that there is a discrepancy between reported values on human drivers' longitudinal deceleration when comparing near-crash situations versus incidents (maneuvers that fall outside nominal driving but are not as aggressive as near-crashes' maneuvers). After analyzing a large NDD in USDOT [29], authors found that only 5% of the analyzed events were near-crash situations, with a maximum average longitudinal deceleration of 7.1 m/s^2. When looking at the other 95% of the data that corresponds to incidents, the reported maximum average longitudinal deceleration is 5.1 m/s^2. As a clarification, incidents in this study were defined as a combination of "crash-relevant conflicts," events that forced a crash avoidance response, and "proximity conflicts," events where absence of avoidance maneuver or responses could result in inappropriate proximity for the driving conditions. Additionally, Klauer, et al. [28], NHTSA [24], and USDOT [29] pointed out that drivers do not usually brake harder than about 6.5 m/s^2 even in emergency situations. This is important to consider for understanding what reasonably foreseeable behavior of drivers is and what is not.

When looking at response time of human drivers, average values range between 0.8 s and 1.3 s. It is worth noting that some of the reviewed documents that analyzed human drivers' response time conducted experiments in a controlled setup, i.e., a simulation facility or a test track. This could potentially mean that drivers were more attentive and aware of the surroundings than the average human driver that may get easily distracted while driving, thus the difference between reported values. Participants may also feel more comfortable and at ease in a driving simulator since there are minimal repercussions from poor performance. Thus, their reaction times may be dampened when compared to real-world events. The work by Blommer, et al. [25] pointed out that drivers' response times were shorter when driving in manual mode compared to when driving with some automation support.

Only one study reported information about vehicles' longitudinal velocity (NHTSA [24]). While the authors reported that the drivers exhibited a mean velocity close to the speed limit with a SD of 1 m/s, they also pointed out that respecting the speed limit was expected from the drivers on the test track.

5. GAPS ON LITERATURE REVIEW

This section discusses gaps and limitations found during the literature review presented in this document.

One of the main gaps found within the reviewed documents, is the under representation of vulnerable road users' studies. Even though this literature review is not extensive and only looked at some of the most relevant and recent technical documents in the literature, studies on human driving behavior were much more prominent than those of pedestrians and/or cyclists. While this may have an underlying reason, such as the fact that the majority of casualties were from two or more vehicles' collision, rather than from collisions involving non-vehicle entities ("Motor Vehicle Fatality Rate in U.S. By Year" [40]), interaction between vehicles and vulnerable road users is very relevant and pertinent for the mass deployment and adoption of ADS technology. Kinematic properties of vulnerable road users, including different vulnerable road user types, besides pedestrians and bicyclists, need to be further studied to help inform the development of ADS interactions with VRUs.

Similarly, a gap on studies about characterization of the kinematic properties of other type of vehicles, such as heavy trucks or public transportation vehicles, was identified. The study of the behavior of different vehicle types can provide important insights since one of the main applications of ADS is the improvement of mobility in shared spaces.

Additionally, 12 studies analyzed data from North America, compared to 5 studies from Europe, and 5 from Asia, for example. The research community should address this effort with road user behavior analysis pertaining to as many regions/ODDs as possible.

Another limitation observed in the studies pertains to the reporting of vehicle speeds with reference to the speed limit of the road in which they are traveling. While some studies provided distribution of vehicle speed of their data samples (NHTSA [24], Xu, et al. [35]), further detail is needed to understand human driver adherence to speed limits and to distinguish the operating envelope of the driving scenarios that the data contemplates. This helps to determine the adequacy of the values to a corresponding ODD for the ADS.

The literature search did not report successful research findings on certain kinematic properties such as longitudinal velocity for vehicles, lateral velocities for bicyclists, response times for bicyclist and lateral velocities and accelerations in pedestrians. The main reason for this is that each study is focused on a different topic and therefore, doing a comprehensive data characterization reporting may not be suitable to the question that authors are trying to answer with their analysis.

A lack of reporting of contextual information, such as road characteristics, road infrastructure, weather conditions, time of day, among others, was also identified. This is particularly important for studies reporting findings from naturalistic data where statistical aggregates often fail to identify the range of sample conditions. Even within a geographic region, variations may exist between subregions (e.g., city vs. suburbs vs. highway). The kinematics of road users may vary significantly and there is great potential for the variability in observed road user behaviors and their values.

This highlights another limitation on the available literature. In order for the results to be useful for automated driving development, they need to be put into context with as many relevant details as possible. This effort might not be possible for some of the published work but leveraging some of the best practices in the industry for characterizing operational design domains (e.g., AVSC Best Practice [9]) when reporting future results would facilitate the application of the reported values to automated driving systems.

In addition, the analysis of the literature review made clear that certain types of driving scenarios have been further studied than others. In particular, longitudinal vehicle interactions have extensively been subject of study for ADAS systems, for example, but lateral interactions have not been equally reported. Given the expectation of ADS systems to perform complex interaction such as lane changes, as well as handling of cut-ins, cut-out, and close interactions with vulnerable road users, it is critical for the community to address this gap. Similarly, the majority of the research has been located in geolocations that have facilitated naturalistic data collection an analysis, such as the United States and certain European countries. This leaves, however, an imbalance in the representation of values across other regions. The research community needs to address this limitation to facilitate the upcoming scalability of ADS-equipped vehicle deployments world-wide.

Finally, another limitation of some of the existing literature is that there is still a lack of understanding of the validity of kinematic values captured in controlled conditions, including experiments where participants anticipate an alert or event, as in Wood, et al. [13], with those captured into the wild. Further research investigating domain transfer of values in simulation to those in closed test facilities and in the wild should help determine the limitations of some of the reported values as well as the accuracy and their generalization.

6. CONCLUSIONS

Recent approaches to safety-related models for ADS make use of assumptions to help determine bounds of kinematic properties associated with interactions between road users in order to derive a safety envelope for the ADS. IEEE Std 2846-2022 has formalized a minimum set of assumptions of kinematic properties of road users' behavior to be considered by safety-related models in certain driving scenarios. However, the standard does not provide guidance on the actual values or ranges of values that different road users, such as pedestrians, vehicles, or bicyclists, can exhibit. Therefore, this document is a first effort in that direction where a review of existing literature was made for comparable measurements and analysis of kinematic properties of road users.

The literature review included technical papers from IEEE Xplore and SAE Mobilus databases as well as studies reported in standard and regulation contributions such as UNECE forums. The selected studies were analyzed and contextualized by geographical location, year, experimental setup, road user types and other applicable characteristics.

A summary of the kinematic properties for pedestrians, bicyclists and vehicles was captured in reference tables, providing concise clarification of the context of the data captured and analyzed. In certain cases, strong consistency across studies was identified such as in the case of pedestrian kinematic values for their longitudinal speed. This correlation across studies and geographies provides supporting evidence towards the use of certain value ranges in assumptions about reasonably foreseeable behavior of pedestrians. In other cases, such as with bicycles, the resulting studies depicted diverse values, such as in the longitudinal accelerations observed in bicyclists. These discrepancies might be related to studies capturing different ranges of behaviors such as cruising bicyclist vs. those initiating movement from a stopped position at an intersection. These cases reveal that a clearer taxonomy of bicyclist behaviors and guidelines for reporting their exhibited behavior would be beneficial for the community.

In other cases, discrepancies might reflect the experimental conditions under which data samples were captured, such as those coming from simulation vs. filed test vs. naturalistic driving data. This indicates that further evidence is needed for determining the validity and applicability of road users' kinematic properties domain transfer. The literature review also identified other limitations such as under-representation of certain types of kinematic properties such as lateral velocities or accelerations of road users which need to be addressed in further research to provide a more complete characterization of road user behaviors. In addition, researchers should also provide a more comprehensive description of the contextual conditions under which the data was gathered and filtered. Certain naturalistic data analyses lacked specificity on relevant information such as road type, road geometry and other environmental conditions such as weather. Understanding the contextual details in which a study took place may have significant impact on determining the applicability of the reported kinematic values to a particular operational design domain of an ADS.

Finally, in order to support the global effort of scalable ADS deployment, the research community should perform active effort to provide further analysis of measurements in under-represented Geolocations such as those located in Asia, Latin America, or Africa. Comparative studies in these geolocations will facilitate our understanding of cultural differences in road user behaviors and spur the necessary modifications to ADS technology to serve the global market.

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