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Adapting the California Vehicle Code into a Machine-Readable Database to Improve Legal Compliance in Automated Driving Systems

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Adapting the California Vehicle Code into a Machine-Readable Database to Improve Legal Compliance in Automated Driving Systems

A thesis submitted in partial satisfaction

of the requirements for the degree Master of Science

in Civil Engineering

by

Matthew Greggory Huffman

2023

ABSTRACT OF THE THESIS

Adapting the California Vehicle Code into a Machine-Readable Database to Improve Legal Compliance in Automated Driving Systems

by

Matthew Greggory Huffman

Master of Science in Civil Engineering

University of California, Los Angeles, 2023

Professor Jiaqi Ma, Chair

The proliferation of automated driving systems in the contemporary vehicular landscape has prompted an increased focus on proper vehicle operation from all stakeholders, including the general public, law enforcement agencies, policy makers, and autonomous vehicle designers. As these automated driving systems advance in complexity and responsibility, they challenge established norms on how the rules of the road are conveyed and interpreted, especially across various jurisdictions and driving cultures. In response to this challenge, this paper introduces an innovative framework for the conversion of text-based vehicle codebooks, currently enshrined in legal terminology dictating human driver behavior, into a machine-readable database conducive to the decision-making algorithms inherent in automated driving systems. Moreover, with this proposed methodology, existing vehicle regulations can be analyzed for ambiguity and coverage,

allowing legislators and autonomous vehicle designers to focus efforts on improving the automated driving legal landscape.

The thesis of Matthew Greggory Huffman is approved.

Sriram Narasimhan

Enrique Andres Lopez Droguett

Jiaqi Ma, Committee Chair

University of California, Los Angeles

2023

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LIST OF ACRONYMS

ADS	Automated Driving System
AV	Autonomous Vehicle
CC	Cruise Control
LKA	Lane Keeping Assistance
AEB	Automatic Emergency Braking
ACC	Adaptive Cruise Control
GPS	Global Positioning System
USDOT	United States Department of Transportation
DAVI	Data For AV Integration
WZDx	Work Zone Data Exchange
UVC	Uniform Vehicle Code
CVC	California Vehicle Code
LACVC	Los Angeles County Vehicle Code
CLAVC	City of Los Angeles Vehicle Code
LLM	Large Language Model
ODD	Operational Design Domain
FHWA	Federal Highway Administration
VRU	Vulnerable Road User

INTRODUCTION

BACKGROUND

Automated driving systems (ADSs) are increasingly becoming more common in vehicles on the road today and, as such, are running into increased scrutiny from the public, law enforcement, and policy makers (USDOT, 2020). From simple cruise control to full self-driving systems, all variations represent advancements in vehicle technologies that are increasing the focus on compliance with the rules of the road. All ADS stakeholders, including road users, automated vehicle (AV) designers, legislators, and law enforcement, must begin to consider how ADSs will understand and abide by existing driving codes and regulations. To this end, this paper presents a novel scheme for converting the existing text-based vehicle codebooks, which currently address human driver behavior via legal jargon, into a machine-readable database that is more easily interpretable by both humans and automated driving systems. This proposed database is subsequently tested for functionality with software simulation, which aims to replicate the planning module of a simple ADS.

To set the stage for any discussion on automated driving systems, it is important to first understand the various levels of ADSs. As shown in Figure 1, ADSs can be classified by their level of autonomy and driver involvement (SAE International, 2021).

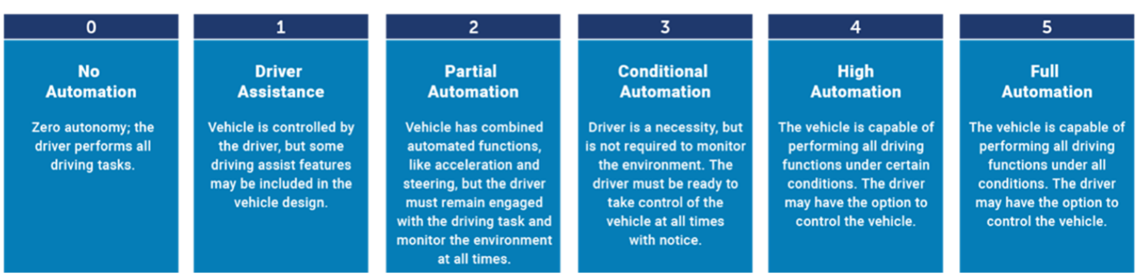


Figure 1 – SAE Autonomy Classifications

ADSs have progressed through these classifications over time, requiring an increasing number of data sources in order to perform their functions both safely and comfortably. For example, in the early days of the first ADSs, systems like cruise control (CC) used just one datum (the vehicle's own speed) to provide a semi-automated and comfortable way to travel long distances (Sears, 2018). As ADSs became more complex, systems like lane keeping assistance (LKA), automatic emergency braking (AEB), and adaptive cruise control (ACC) began to require more data sources like low-definition video and proximity sensors to inform onboard computers on steering position and distance from other vehicles (Weaver, et al., 2022), (NHTSA, 2023).

In today's most advanced ADSs, these data requirements now include high-definition camera video, radar, digital maps, GPS, vehicle telemetry, and more. Because modern ADSs are provided with this data, they can function comfortably in level 2 or 3 autonomy with some input occasionally required from a human driver (Cusumano, M. 2020). This progression thus far in ADS technology has led to preliminary testing of concepts like automated taxis and trucking, robotic factories and warehouses, drone services, and more. However, since level 4 and 5 autonomies require complete control of the vehicle by an ADS, there can be no room for uncertainty. It is plausible that ADS technology will continue to require additional new types of data to remove this uncertainty and reach the highest levels of full autonomy.

Currently, there is little existing regulations on ADS on-road behaviors from US federal or state entities. Most ADS regulation today focuses on the background information, that is, the identification, registration, permitting, reporting, and insuring of the vehicles themselves. Some legal entities also have established testing ground rules and procedures around interaction with traffic and law enforcement officials (DMV CA, 2023). However, there is limited work involving interpreting the rules of the road for the function of ADSs.

A review of current ADS regulation development in places like Australia, Europe, and China reveals a similar story. These regulations again focus on rollout, classification, and testing procedures but with some additional focus on compliance and data security (Eastman, et al., 2023). One of the most extensive databases involving ADS development is SafetyPool which is a global collection of various operating scenarios and the associated data collected from the vehicles themselves during these scenarios. This data can be collectively used by ADS developers to extend the training dataset to improve ADS performance (SafetyPool, 2023). This approach has facilitated communication and data sharing between stakeholders worldwide but is limited in that it isn't targeted toward addressing specific regulatory differences between jurisdictions. Moreover, SafetyPool's data is of the more traditional ADS type, resulting in a gap of new and emerging data that could help push the abilities of ADSs toward higher levels of autonomy.

With the increased focus on the liability side of automated vehicles, it is likely this data will come in the form of rules and regulations specifically designed for the on-the-road function of ADSs (Hancock et al., 2019). Notably, the US Department of Transportation (USDOT) has recently identified three priority focuses for the future of ADS technology, one of which is to "Modernize the Regulatory Environment" (USDOT Comprehensive Plan, 2021). This focus has led to research efforts, bolstered by the Federal Highway Administration (FHWA), into the creation of a modern regulatory database for ADSs. This report supports a part of that effort and builds upon work being done at the University of California, Los Angeles (UCLA) under Dr. Jiaqi Ma (Garrett et al., 2020). Research here has supported the development of various emerging transportation data and data sharing programs like Data For AV Integration (DAVI), Work Zone Data Exchange (WZDx), and more. These programs have facilitated increased communications between ADS stakeholders and governmental bodies for the purposes of AV data sharing and are increasing the pace at which innovation occurs. This report aims to further these efforts by providing a database and subsequent analysis of the California driving codes most relevant to ADS development. At a minimum, this will allow future research to efficiently select driving operations and regulations for ADS testing in both simulation and physical world. At a maximum, this report could be useful for additional efforts into ADS legislation creation and reform.

CURRENT GAPS

Currently, the latest ADSs use advanced machine learning algorithms to train and execute good operating behavior (FHWA ML, 2022). These algorithms process a plethora of data inputs from various sensors throughout the vehicle and make planning decisions that will result in the highest possible "score" as decided by the algorithm. This score is deduced from a weighting of potential operating factors that maximizes a variety of design objectives including safety, comfort, and navigational accuracy (OPS-FHWA, 2023). However, algorithms are only as good as the data used to train them. In "end-to-end" ADSs, a more advanced style of ADS used solely or in conjunction with the more classical "modular" style of ADS, data is collected by the vehicles themselves while on "training runs" in which a human driver operates a vehicle in a variety of traffic conditions and allows the ADS to learn proper driving behavior by observing the operation of the vehicle by a human driver (Tampuu, A, et al, 2021), (LeCun, et al, 2015).

This training method, while effective, still relies on a human driver's knowledge and execution of good driving behavior. Common mistakes made by human drivers can be thus passed onto the algorithm's behavior accidently. Additionally, training runs can require numerous repetitions before an ADS "learns" the proper behavior and the use of trained human drivers for this purpose is difficult to scale, especially for every scenario in every jurisdiction at every time of day. This training method can also mean rare driving conditions (e.g. fringe legal scenarios) are not trained as often or are only trained after they occur, resulting reactionary training (Peng et al, 2021). While simulation can preemptively address some of these unique training cases, there is still a need to collect similar real-world data in order to simulate. This imperfect human and delayed connection between ADS input data, training, and good ADS behavior represents a significant gap in the AV training and operating environment, prompting a need for additional immediate input data that can provide feedback to operating ADSs.

ADS training input data can be collected from vehicles in a variety of geographic locations and jurisdictions (e.g., SafetyPool). It is unclear from existing literature whether private AV companies are geographically separating this data before use in training, however, the incentive would be to combine the datasets in the interest of increasing total training knowledge. This combination approach, while effective, does not allow for differences in driving regulations across jurisdictions. In the Unites States, rules and regulations governing vehicle traffic behavior are not legislated at the federal level. Instead, each state is responsible for developing and enforcing a base vehicle codebook. In turn, local entities and municipalities impose upon or modify this state codebook in order to develop their own codes for vehicle behavior within their jurisdiction. This can result in a multitude of differing regulations that ADSs will need to be able to obey as they navigate from jurisdiction to jurisdiction.

For example, right turns at red traffic signals are permitted by some jurisdictions but not others. An ADS trained on observational input data from jurisdictions that mostly allow for right turns at red signals could unintentionally break the law in cities where this is not allowed. Therefore, it is necessary for an ADS rules system, like the ADS database proposed herein, to provide the “ground truth” rule for the applicable operating jurisdiction. Utilizing the database in the prior example, would result in an ADS that understood which cities allow for right turns at red lights and which do not. Not only could the database’s output (e.g., legal, or not legal for a given planned scenario) be used for immediate feedback/correction to the ADS during operation, but also for the labeling of scenarios in training for more accurate learning.

Furthermore, if a given jurisdiction wanted to update their driving regulations to change an existing code, then this change would need to be promptly communicated to an ADS. Such a change may not be recognized by typical ADS training methods, which aim to emulate the previously trained on driving operation data (Luca et al, 2022). This training data is necessarily an aggregate of past operations and any changes in operational rules are not noticed without manual intervention or until enough re-training and observation has occurred to change the algorithm’s weighting system for a different behavior. Thus, there is necessarily a need for jurisdiction specific input data that allows an ADS to make proper operating decisions according to the applicable rule in real time. The next section presents a methodology for creating, implementing, and testing an ADS database that can be used as input data for next generation ADSs.

METHODOLOGY

FORMAT

The produced ADS database was designed to be interpreted by software that could be operating in real-time on the road. This meant that the database needed to be compact in size, have low latency, and be easily queried, with some consideration given to complex data types. For this reason, a simple non-relational database format commonly known as "Key-Value" was chosen to form the ADS database (AWS, 2023). Table 1 below demonstrates an example key-value database in the context of driving regulations. Multiple inputs, when matched to the correct keys, correspond to a given value and output.

Key 1	Key 2	Key 3	Value
Current Driving Scenario	Current Ego Vehicle Speed (mph)	Observed Maximum Speed Limit (mph)	Resulting Output Legality
Traveling	30	45	TRUE

Table 1 – Example Key-Value Database

Essentially, a Key-Value database allows for an ADS to query with a list of keys and receive a legality output value that can be integrated with the planning component of all ADSs. This style search can also handle multiple outputs in scenarios where actions are legal or illegal in varying contexts where keys are missing or unknown. This search is near instantaneous when compared to the existing method of manually looking through hundreds of code texts and/or consultation with legal counsel. Recently, many jurisdictions have moved their codes into electronic format which allows for keyword look-up but with no greater search granularity. The proposed database would allow for filtering of codes by specific driving operation characteristics like speed, school zones, overtaking, planned scenario, and more. Additionally, this style database could be used for any legislative code conversion with potential benefits for improving the efficiency of the legal system even outside of ADSs and vehicle operation.

ORGANIZATION

Once a database format was chosen, the next step was to organize and translate the existing vehicle codes. This work began by identifying the commonalities between various vehicle codebooks. The codebooks used for analysis were the Uniform Vehicle Code (UVC), the California Vehicle Code (CVC), the Los Angeles County Vehicle Code (LACVC), and the City of Los Angeles Vehicle Code (CLAVC). With the exception of the UVC, which holds no jurisdictional power and is merely a federal recommendation to states, these vehicle codes represent the rules and regulations for a typical vehicle operating in and around the City of Los Angeles and Los Angeles County. These codes have the force and effect of law within their jurisdictions (Bavis, 2013). The figure 2 below demonstrates a vehicle operating across this hierarchy. At all times, unless otherwise specified, the CVC establishes the ground truth rules for vehicle operation in the state of California. However, where the CVC leaves room to do so, city & county jurisdictions can modify or supplement these driving codes for their own purposes.

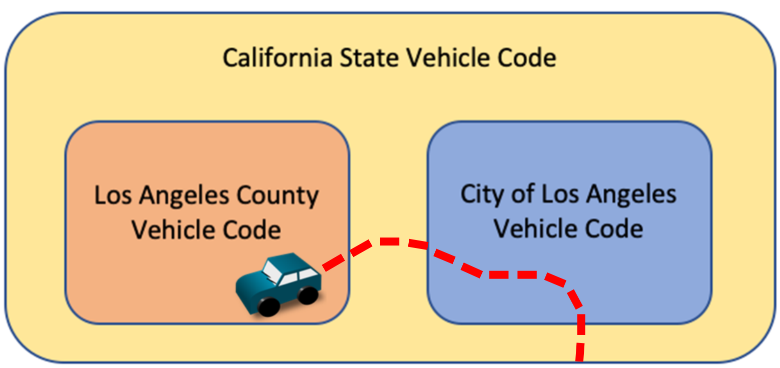


Figure 2 – Driving Through the Hierarchy of California Vehicle Jurisdictions

To begin the consolidation and conversion process from all legislation codes to database, common organizational factors between the different codes were first considered. The relevant code subsections were extracted and organized to find similarities within the codes. As seen in the figure 3 below, the organization of these codes among the selected jurisdictions is relatively similar and allows a starting point for organizing a common ADS database.

CVC	LACVC	CLAVC	Summary Legislative Classifications
Obedience To And Effect Of Traffic Laws	General Provisions, Definitions, Enforcement	Obedience To Traffic Regulations	Obedience To And Effect Of Traffic Laws
Traffic Signs, Signals, And Markings	Traffic Signs And Signals	Traffic Control Devices	Traffic Control Devices
Driving, Overtaking, And Passing	-	-	Driving, Overtaking, And Passing
Right-Of-Way	-	-	Right Of Way
Pedestrians' Rights and Duties	-	Pedestrians	Pedestrian's Rights And Duties
Turning And Stopping And Turning Signals	Turning Movements	Turning Movemens	Turning Movements
Speed Laws	Speed Limits	-	Speed Laws
-	Miscellaneous Regulations	Miscellaneous Driving Rules	Miscellaneous Driving Rules
Special Stops Required	Boulevard Stops	Special Stops Required	Special Stops Required
Stopping, Standing, And Parking	Stopping, Standing, and Parking	Stopping, Standing, And Parking	Stopping, Standing, And Parking
Removal Of Parked And Abandoned Vehicles	Trespass By Motor Vehicles	Terminal Access For Interstate Trucks	
Parking Lots	Repossession of Motor Vehicles	Restricted Use Of Certain Streets	
Public Offenses	Miscellaneous Regulations	One Way Streets And Alleys	
Vehicle Crossings And Toll Highways	Cruising	Method Of Parking	
	Abandoned Or Inoperative Vehicles	Stopping For Loading And Unloading Only	
	Traffic On Private Streets	Parking Prohibited Or Limited	
	Private Roads Open For Public Use	Penalties And Effect Of Chapter	
	Housing Authority Traffic Regulations	Schedules Of Designated Streets Referred To In Chapter [Speed Zone Schedules]	
	Weight Limits	Miscellaneous [Non-Driving]	
	Interstate Truck Terminal Access Routes	Traffic Regulations In Park	
	Crosswalks and Bicycle Lanes	Traffic Regulations In the Harbor District	

Figure 3 – Organization of ADS Database by Codebook Commonalities

This paper focuses primarily on the more pertinent and common driving codes in order to create a database that is representative at all municipal levels. A brief review of the resulting common code categories showed that not every section contains driving operation related codes. For example, “Obedience To and Effect of Traffic Laws” covers primarily the legal authority of traffic and law officials while “Pedestrian’s Rights and Duties” emphasizes pedestrian behavior around roads. However, both of these (as well as all the sections) do include codes that should be incorporated into an ADS database in future work. The codes within the subsections “Driving, Overtaking, and Passing”, “Speed Laws”, and “Special Stops Required” were selected to be the first focus of this initial ADS database as these common codes contain the most driving related regulations.

BREAKDOWN

A robust data extraction process was developed to break down a single text code into its database parts. These parts include features like metadata, applicability, rule vagueness, key characteristics, exceptions, and legal outputs. The flowchart for this process is shown below in Figure 5. OpenAI's GPT-4, an advanced Large Language Model (LLM), was tested to demonstrate the feasibility of an automated approach to this conversion process. Development of an automated text-to-database conversion software using LLMs was outside the scope of this paper but subsequent sections in this paper discuss the findings from preliminary testing of a LLM text-to-database conversion process in further detail. For the purposes of this paper, the majority of the database was generated through the manual process described herein.

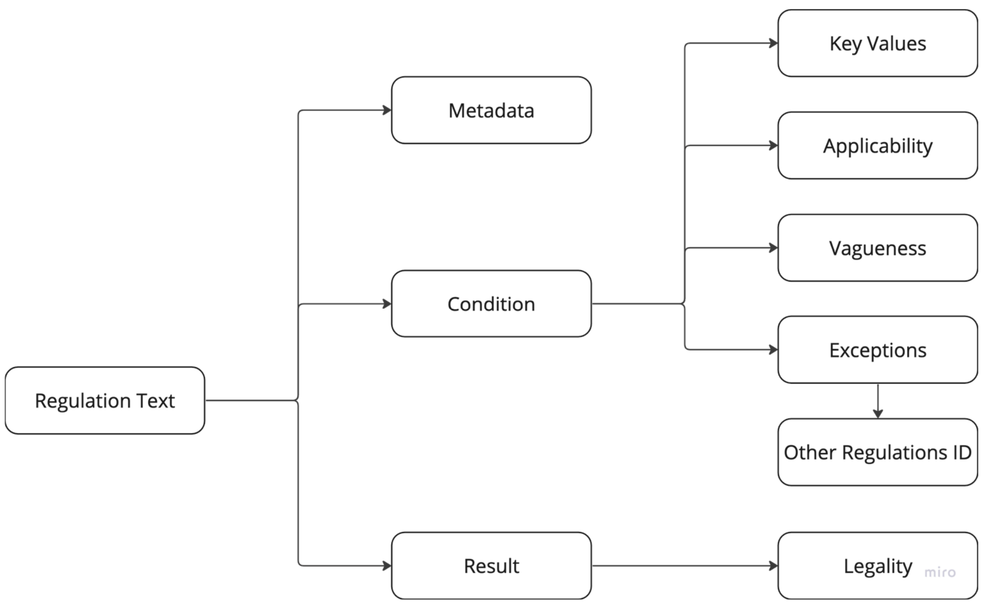
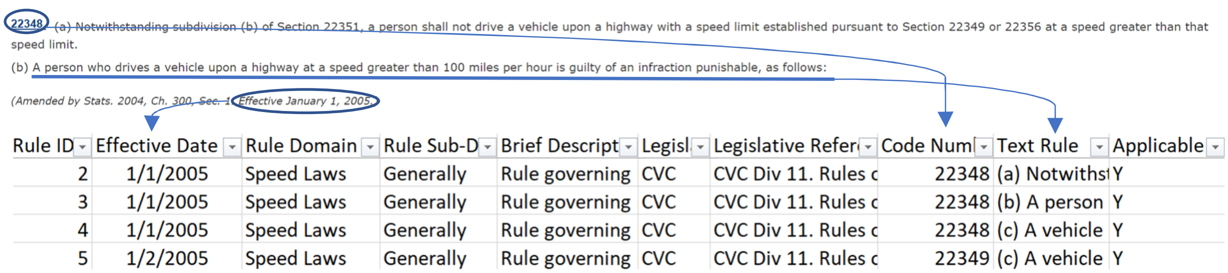


Figure 4 – Code Extraction Flowchart

To begin, metadata was collected from the codebook for each code and stored in the database. Collecting metadata is an essential good data governance practice that allows for a deeper understanding of the data and extends the datasets useable life into future applications

(FHWA InfoMaterials, 2021). The metadata recorded during the conversion process for this each code included source vehicle codebook, date the code became effective, code location within the codebook, the literal text of the code itself, a brief description of the code, and a unique number identifier for the purposes of exception handling and post processing of the resultant database. An example of this collection process is provided below in figure 4.



22348 (a) Notwithstanding subdivision (b) of Section 22351, a person shall not drive a vehicle upon a highway with a speed limit established pursuant to Section 22349 or 22356 at a speed greater than that speed limit.

(b) A person who drives a vehicle upon a highway at a speed greater than 100 miles per hour is guilty of an infraction punishable, as follows:

(Amended by Stats. 2004, Ch. 300, Sec. 1. Effective January 1, 2005.

Rule ID	Effective Date	Rule Domain	Rule Sub-D	Brief Descript	Legisl	Legislative Refer	Code Num	Text Rule	Applicable
2	1/1/2005	Speed Laws	Generally	Rule governing	CVC	CVC Div 11. Rules c	22348	(a) Notwiths	Y
3	1/1/2005	Speed Laws	Generally	Rule governing	CVC	CVC Div 11. Rules c	22348	(b) A person	Y
4	1/1/2005	Speed Laws	Generally	Rule governing	CVC	CVC Div 11. Rules c	22348	(c) A vehicle	Y
5	1/2/2005	Speed Laws	Generally	Rule governing	CVC	CVC Div 11. Rules c	22349	(c) A vehicle	Y

Figure 5 – Metadata Collection

Next, the literal text of the code was analyzed. After review of the codes, it was found that many contain essentially two parts, one or several "Conditions" and a "Result". This structure lends itself to the "If-Then" format (that is, if "Conditions" then "Result") which is also known as Boolean Logic. Additionally, this format pairs well with the chosen "Key-Value" database format with "Conditions" equating to keys and "Result" translating to the output value.

To split the code text into these 2 parts, a review and label process was used. An example of the "Conditions" and "Result" division from code text is shown below in table 3 with the two parts of the text highlighted in yellow and green respectively.

<table>
<tr><td colspan="2">CVC 22348.b Code Text</td></tr>
<tr><td colspan="2">"A person who drives a vehicle upon a highway at a speed greater than 100 miles per hour is guilty of an infraction punishable, as follows"</td></tr>
<tr><td>Condition</td><td>Result</td></tr>
<tr><td>If a person drives a vehicle upon a highway at a speed greater than 100 miles per hour</td><td>It is illegal to operate the vehicle at such speeds</td></tr>
</table>

Table 2 – Example Conditions-Result Division

Note that in some cases, codes and or code subsections were not applicable to vehicle operation and instead pertained to administrative details such as how jurisdictions could enforce and/or penalize certain driver behavior. These codes were classified not applicable and were not processed further. Additionally, some codes were simply too complex or covered operating concepts to niche to be properly converted within the scope of this paper. The failure of the methodology to convert these complicated codes into database form is one such metric for evaluating the performance of the proposed methodology, as discussed in the results section.

The next step in the code text conversion process was to separate the "Conditions" part into its key characteristics. Key characteristics are the scenario specific features that create the ADS operational design domain (ODD). Said differently, key characteristics are the "inputs" for the ADS decision making process and could be considered the way an ADS describes the world it's currently operating in. These "inputs" have traditionally included characteristics like the ego vehicle's current telemetry, current visibility, existing signage, and the movement of other vehicles. Previous research has identified promising key characteristics, like those listed above, that were used as a starting point for converting the "Conditions" text into its key subparts. However, during the conversion process, it was realized that actual driver regulations focus on more key characteristics than previously considered. For example, total key characteristics after database completion numbered 60 distinct items that affect compliance to driving codes. More discussion of these additional findings can be found in the results section below.

Continuing with the previous example code "Conditions" text, its key characteristics are shown below in table 3.

"If a person drives a vehicle upon a highway at a speed greater than 100 miles per hour"	
Key Characteristics	
Road Type: Highway	Ego Speed (mph): >100

Table 3 – Example Key Characteristics Division

Finally, consideration was given to the quality of the conversion process as not every code was perfectly translatable into a database entry. Consistently, during roundtable discussions with ADS stakeholders led by the FHWA (referred to as the National Dialogue on Highway Automation), many tech and policy leaders were concerned by the vagueness of some current vehicle regulations and how they might be applied to AVs. For instance, terms like "reasonable" and "prudent speeds" are commonplace throughout existing vehicle codebooks and can represent complications in rule intention. This vagueness can lead to biased enforcement of the rules and difficulty evaluating an AV's adherence to proper driving behavior. To understand the extent of this vagueness and identify a starting point for future vehicle code legislative changes, a vagueness score was assigned to each code according to the framework shown in Table 4 below.

Vagueness Score	Justification For Score
0	No vagueness: Numerical or objective definitions are provided with no questions as to intent.
1	Little vagueness: Rule qualifiers can be deduced by context with little question as to intent.
2	High vagueness: Requirements depend on subjective interpretation of existing conditions, "safe" operations, and/or the presence of a human director.

Table 4 – Vagueness Scoring Framework

The resulting database entry (abbreviated) for this example code is shown below in table 5. An ADS would use this database entry to augment its decision-making process in the following way. First, the ADS would receive from its perception and planning module, all proposed key values from its ODD (e.g., what it's "seeing", what it plans to do, which jurisdiction its operating in, etc.). The ADS would match these key values to key values in the proper jurisdictional Key-Value ADS database. In this example, occurring on a California state road, if one of the proposed scenarios included highway traveling, with an ego speed greater than 100 mph, the California vehicle code database would return a FALSE legal output and the ADS could remove (or severely demote) this proposed scenario within its decision scoring process.

						Key Values	
Code Text	Condition	Result	Legality	Proposed Scenario	Vagueness Score	Road Type	Ego Speed (mph)
"A person who drives a vehicle upon a highway at a speed greater than 100 miles per hour is guilty of an infraction punishable, as follows:"	"A person who drives a vehicle upon a highway at a speed greater than 100 miles per hour."	"It is illegal to operate the vehicle at such speeds	FALSE	Traveling	0	High way	>100

Table 5 – Example Abbreviated ADS Database Entry

ADS DATABASE VALIDATION

ADSs are the product of a variety of different systems working in harmony. These systems include sensing, perception, mission planning, motion planning, and actuation command. Within this stack of systems, the mission planning module carries significant weight. This module is responsible for developing the series of goals that will facilitate the vehicle to its destination in a safe and legal manner. It is at this module that the addition of the ADS regulation data can be tested and validated for usefulness.

Integration

To simulate this mission planning component, the OpenCDA platform developed by UCLA is used. This platform is a full-stack simulation software that incorporates the regular ADS components (e.g., perception, planning, control) as well as cooperative driving automation (CDA) pipelines to validate C2X technology. This software tests the ability for a planning system that can not only consume the regulation data from the proposed database but also implement these regulations within its decision matrix.

Figure 6 below displays the overarching framework associated with the validation of the proposed regulation database and the suggested coordinated efforts of future ADSs that utilize a regulation database. The upper section (Sense, Plan, Actuation, and Control components) encompasses the traditional ADS software stack. The lower section represents the required components necessary for an ADS to consume, interpret, and utilize driving regulations. The ADS platform will integrate the regulations in the following way. First, the ADS will gather observations on the current environment (signage, striping, ego trajectories, other vehicles, etc.) from the Sense component. Then, the ADS will reference the current and planned operating scenarios (traveling, following, overtaking, turning, etc.) from the Plan stack. Finally, the proposed regulations software will take these inputs and use them as keys in the key-value regulation database. Importantly, the ADS will utilize the proper regulation database for the jurisdiction it is operating in, using its own location data and on-board maps of jurisdictional boundaries.

The ADS will query all proposed scenarios in the regulation database and will receive an output on each scenario's legality. This output, definitively legal or illegal, is then fed back to the Plan software for use in the decision matrix. This feedback loop is common in emerging ADSs. Legal proposed scenarios are scored better while illegal scenarios are penalized. It's important to note that while some planned scenarios may have poor regulation compliance scores due to illegal maneuvers, they may still score the best overall as safety is the highest factor impacting the decision process (e.g., swerve across solid lane line to avoid sudden object in road). Further discussion on the technical components of this decision-making process is included in subsequent sections.

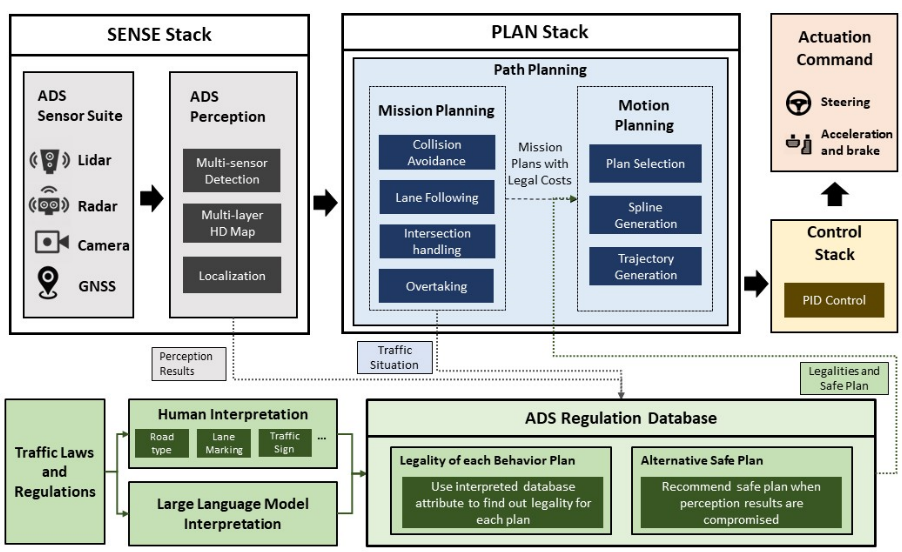


Figure 6 – ADS Testing Framework

Regardless, this introduction of regulations into ADSs still represents a significant deviation from contemporary ADS software. While leading-edge ADSs like CARMA℠, Autoware™, and Apollo™ use a similar feedback loop for strategic (general mission) and tactical planning (local motion), they do not reference any regulations tied to existing legislation. The OpenCDA stack allows for the addition of this ADS regulations component and the process is validated in simulation testing.

Mission Planning Superstates

Figure 7 below illustrates the flow between four primary superstates governing the autonomous driving system (ADS) in the OpenCDA testing system: lane following, intersection handling, overtaking, and collision avoidance. It all begins with the ADS pinpointing its current location and user-specified destination, establishing a comprehensive global route encompassing road and lane segments. From here, the ADS embarks on lane following, strategizing its actions. Intersections along the route trigger a shift to the intersection handling superstate, managing navigation through intersections before reverting back to lane following. Overtaking, distinct from lane changing, involves higher speeds and aligning with the calculated global route, accommodating two consecutive lane changes and stricter traffic rules on specific road stretches.

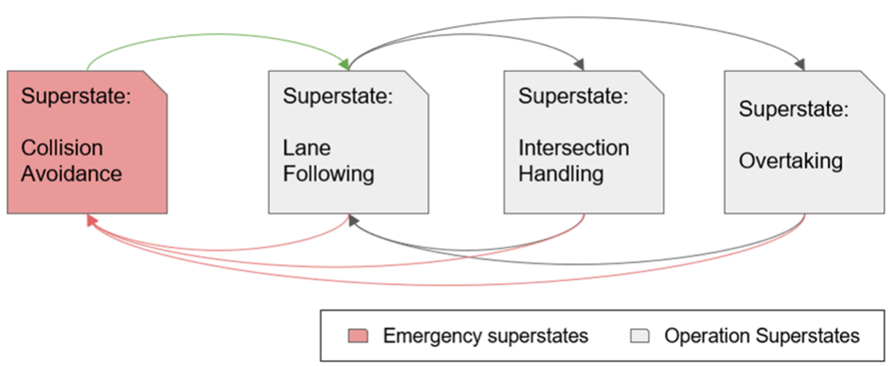


Figure 7 – Superstate Transition Diagram

The collision avoidance superstate takes precedence in safety-critical situations, instantly transitioning from any other state to avert collisions. Once safety concerns are resolved, it seamlessly returns to lane following to resume its course toward the destination. Within these superstates is more specific motion planning, specifically vehicle trajectory generation. The technical components of this are discussed in the following section.

Tactical Motion Planning

After the target waypoints from the mission planning component have been generated, an ADS algorithm creates a proposed path from a set of N waypoints. This cubic spline interpolated curve, created from these points, is the subsequent trajectory of the ADS controlled vehicle. In the current research proposed by the UCLA Mobility Lab, N is a flexible number which represents an improved over traditional ADS systems, which used a fixed number (e.g., the CARLA simulator). An example of this routing is shown below in figure 8.

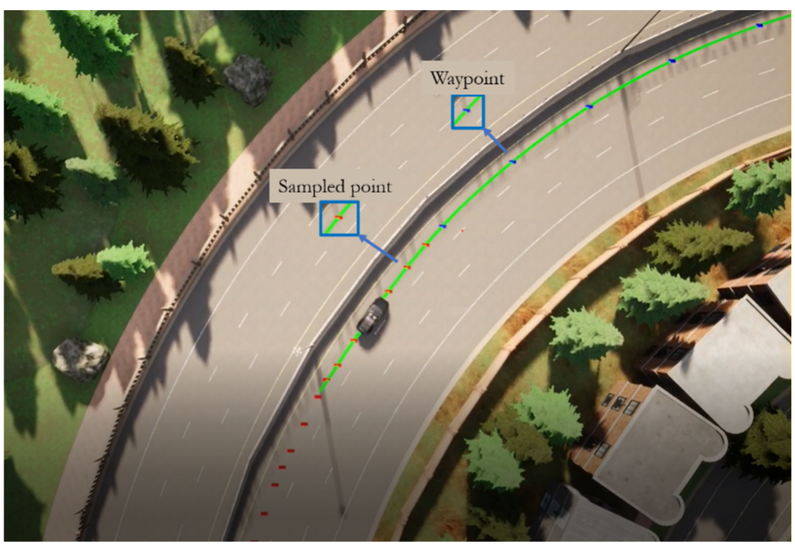


Figure 8 – Illustration of Trajectory Planning

This proposed flexibility provides room for adaption to different road curves and speeds, and possible deviations for cyclists, objects, and other features. As long as the proposed cubic spline curve scores the highest as determined by the ADS cost function, the vehicle will proceed along this path. This cost function will be described in additional detail in the following section. Further detail on the trajectory path generation and tactical motion can be found in the Mobility Lab OpenCDA paper (Xu, R., et al, 2021).

Cost Function Evaluation

As referenced previously, a cost function is a critical part of an ADS trajectory planning, decision making process, and machine learning algorithms in general. At its simplest form, a cost function combines a variety of criteria into a "score" for a given proposed plan. These scores can then be compared against other proposed plans to determine the best scoring plan for use in vehicle path determining. Contemporary ADS cost functions evaluate criteria including safety (risk of collision of unsafe conditions), comfort (rate of acceleration, deceleration, and jerk), and progress toward the navigation goal (distance and/or time toward objective). Typical cost function evaluation formulae 1 – 2 are shown below (Xu, H., et al, 2023).

$$C_{total}(P_i) = Normalized\left(\sum_{category} C_{category}(P_i)\right) \quad (1)$$

Where,

$C =$ cost score.

$P_i =$ available plan.

$category \in \{legal, safety, comfort, distance\}$

$$Normalized(C) = \frac{C - \min C}{\max C - \min C} \quad (2)$$

The inclusion of vehicle regulations into ADS planning stacks presents the novel addition of legality into the cost functions evaluated criteria. The proposed plan can be evaluated using the ADS regulation database for a legality score, which is then incorporated into the overall score by the cost function. For example, a proposed path that breaks no regulations would be favored over a proposed path that breaks some regulations. Again, it is necessary to note that some paths that break regulations could score higher overall due to the heavy weighting of safety in ADS planning (e.g. swerving across double white line to avoid object in road vs. rapid unsafe braking event).

This inclusion of legality into the cost function criteria would augment the decision formulae in the following way as shown in equations 3 – 4 below. This represents the proposed formulae to measure and evaluate the legality criteria within the ADS cost function.

$$W_{legal}(P_i) = \{\, \mathbf{1}\ if\ P_i\ is\ legal; \mathbf{5}\ if\ P_i\ is\ illegal\} \quad (3)$$

$$C_{legal}(P_i) = Normalized(W_{legal}(P_i) * K_{legal}) \quad (4)$$

Where,

W_{legal} = different weight for plan P_i based on its legality determination result.

K_{legal} = a constant numerical cost score for legality consideration.

C_{legal} = *weighted* cost score for legality consideration.

Additionally, safety cost functions could be modified to include values provided alongside the ADS regulation database for vehicle trajectory (speed, acceleration, deceleration, curvature, etc.). Safety is the priority for many traffic regulations but unfortunately, many are ambiguous or only refer to a “safe” speed. Incorporating trajectory values alongside ADS regulations could provide ADSs with specific benchmark values to better weight their cost functions. An example of this proposed cost function is shown below in equation 5.

$$C_{safety}(P_i) = Normalized\,(W_{safety} \times [A_{P_i} - A^*, D_{P_i} - D^*, V_{P_i} - V^*, S_{P_i} - S^*]) \qquad (4)$$

Where:

C_{safety} = Cost score for safety concern.

W_{safety} = A vector weight for calculating the safety cost score.

A_{P_i} = Average acceleration of plan P_i.

D_{P_i} = Average deceleration of plan P_i.

V_{P_i} = Average speed of plan P_i.

S_{P_i} = Maximum curvature of plan P_i.

A^* = Benchmark value for acceleration.

D^* = Benchmark value for deceleration.

V^* = Benchmark value for speed.

S^* = Benchmark value for curvature.

Similarly, comfort is a relevant part of driving behavior and can the ADS cost functions can be improved by a set of benchmarks provided alongside the ADS regulations database. This would allow for acceleration and deceleration values that could better guide ADS planning where currently there are none. The proposed cost functions for comfort are described below in equation 5.

$$C_{comfort}(P_i) = Normalized(W_{comfort} \times [A_{P_i} - A^*, D_{P_i} - D^*]) \qquad (5)$$

Where:

$C_{comfort}$ = Cost score for comfort concern.

$W_{comfort}$ = A vector weight for calculating the comfort cost score.

A_{P_i} = Average acceleration of plan P_i.

D_{P_i} = Average deceleration of plan P_i.

A^* = Benchmark value for acceleration.

D^* = Benchmark value for deceleration.

Finally, progress to objective, easily thought of as the distance from the navigational goal, is captured by cost functions that are subsequently fed into the overall score for a given proposed path. The given ADS progress cost function equations, used in this paper's validation ADS simulation, are shown below in equations 6 – 7. Note that the distance to goal, typically calculated using the Euclidean distance from ego vehicle to navigational goal, is instead calculated using the Frenet coordinate system to compare the distance from the goal along the proposed path. This method provides more accurate scoring as Euclidean distance may not always equate to a feasible path or route (Han, X., 2023).

$$R(P_i) = search(Wp_{P_i}, Wp_{goal}) \tag{6}$$

$$C_{distance}(P_i) = Normalized(W_{distance} * length(R(P_i))) \tag{7}$$

Where:

$R(P_i)$ = The global topology route from plan P_i's target waypoint to global navigation goal.

Wp_{P_i} = Plan P_i's target waypoint.

Wp_{goal} = The global navigation goal.

$C_{distance}$ = Cost score for distance to navigation goal concern.

$W_{distance}$ = A numerical weight for calculating the distance cost score.

$search()$ = Function to search for all topology routes between two waypoints and return the shortest one.

$length()$ = Function to find the down-track distance of a topology route.

VALIDATION SCENARIO

Naturally, simulation testing cannot capture the full extent of the complexities of on-road vehicle testing but this report aims to demonstrate a proof of concept for subsequent ADS and regulation database efforts. To provide as realistic a scenario as possible, the following operating domain and objective is created: The ADS equipped vehicle spawns into the simulation in the right most lane of a multi lane one way road, traveling 35 mph. There is a cyclist ahead traveling in the same lane and direction and the ADS vehicle's objective is to continue traveling down the road. This scenario is visualized by figure 6 below.

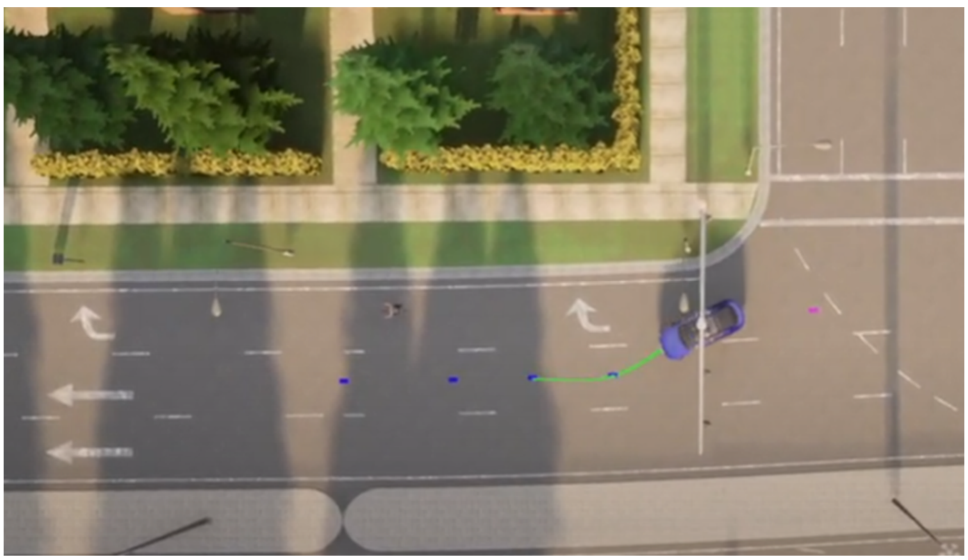


Figure 9 – OpenCDA Simulated Scenario

This scenario will test the ability of the ADS to recognize the cyclist, reference, and adhere to the legally required minimum spacing (3 ft) between vehicle and cyclist while following all other applicable regulations. This will necessarily require the ADS to facilitate overtaking and changing of lanes when safe and legal to do so. This overlapping consulting of regulations by the ADS is critical to test as many on-road scenarios do require evaluating numerous regulations simultaneously. This simulation will test the ADS's ability to recognize all regulations per the database and decide the best possible path in accordance with safe and legal operation.

RESULTS

The completed ADS database for the studied sections of the California Vehicle Code has been posted and available publicly on the internet at the following location:

https://github.com/massgravityheight/ADS_REGULATIONS.git

Importantly, the database format allows for easy analysis of the original vehicle code itself, including on metrics like code applicability, code vagueness, key characteristic importance, and priority codes. In addition to the creation of a conversion methodology and sample ADS database, the second aim of this report is to review the existing driving code and identify areas of focus for ADS stakeholders, including law and policy makers. Insights from the conversion process (including LLM testing) and the completed ADS database will be discussed in these following sections.

LLM CONVERSION TESTING

After experimentation with a variety of LLM prompt techniques the following observations were of note that could aid future development of an automated conversion process using LLMs. Attempts with zero or few shot prompts were studied to determine whether GPT-4 could convert text-based codes into the proposed database format (Han, X., et al, 2023).

Zero Shot Prompting

Zero shot prompting refers to the fact that the LLM has seen no prior data relevant to the requested prompt. This could be thought of as a baseline case from which additional guidance prompting or few shot prompting could follow to increase accuracy and performance. This paper tested zero shot prompting with CVC regulation 21760.c shown below in Table 6:

CVC – 21760.c
“A driver of a motor vehicle shall not overtake or pass a bicycle proceeding in the same direction on a highway at a distance of less than three feet between any part of the motor vehicle and any part of the bicycle or its operator.”

Table 6 – CVC 21760.C

The input for GPT-4 zero shot prompting was the above regulation combined with the comprehensive list of condition keys from the proposed database and a request to identify and label the relevant sections of the regulation with the condition keys. GPT-4 was also instructed to return N/A for any irrelevant condition keys.

Impressively, the LLM was able to return a list of condition keys and their values from the provided regulation. Importantly, it was also able to identify the result (i.e., output) of the regulation. Table 7 demonstrates the returned data from the LLM.

Condition Key	Value
Current Scenario	Approaching Cyclist
Planned Scenario	Overtaking Cyclist
Distance to Cyclist/Scooter	3 feet
Vehicle Speed	60mph
Pavement Marking	Solid Line
Result	Illegal

Table 7 – Zero Shot LLM Response

Note that generated response does not entirely meet the specifications. The “Distance to Cyclist/Scooter” condition key was returned as “3 feet” which does not completely capture the intention of the vehicle regulation’s “less than” condition. The returned form of the key value would only return the regulation result of “illegal” if the distance between cyclist and vehicle was 3 feet exactly, which is not the proper interpretation. Additionally, the zero shot prompt response misses the condition key “Road Type” which should have returned a value of “Highway”. The distinction between various road types was found to be significant in regulation and scenario applicability but the LLM may have struggled due to the broad range of roadways that can be described as highways within the English vernacular. The LLM also returned some hallucinated data with "Vehicle Speed" and "Pavement Marking" being given values that are not contained in the provided regulation. Nonetheless, the errors in conversion may be reduced with subsequent prompting and fine tuning. This "few shot" prompting is discussed in the next section.

Few Shot Prompting

In few shot prompting, the previously provided response is fed back into the LLM with additional requested adjustments. In the testing performed for this paper, the following revision was prompted: "*Reconsider the scenario in terms of road type.*". The LLM was able to produce a more accurate result that included the presence of the "road type" condition key and "highway" key value. The LLM was also asked to verify whether the provided regulation contained references to vehicle speed or lane markings and was successful in removing these condition key values from its output. This output properly matched the values contained in the ADS regulation database that was generated by hand, indicating a successful conversion using GPT-4, albeit with some additional prompting.

Overall, this demonstrates the model's effectiveness as a tool for extracting relevant information from text-based data into database formats that software can then use to improve compliance with vehicle regulations. The use of few shot prompting with GPT-4 shows promise as a method for developing automated conversion processes for the conversion of vehicle codes and other text heavy regulations at scale. With proper fine-tuning of GPT-4 prompting, this paper demonstrates an automated conversion process using LLMs is achievable and should be studied in future research.

DATABASE ANALYSIS AND OBSERVATIONS

Once the studied regulations are completely converted and the resulting ADS regulation database generated, several observations and insights can be gathered quickly, an important benefit of converting the codes into database format. These observations are reviewed in the following sections and a discussion on the “success” of the proposed conversion methodology is provided.

Applicability

The first metric reviewed was the total applicability of vehicle codes for actual vehicle operation. This metric can be used as a type of validation for the success of the proposed methodology. Applicable codes pertained specifically to the proper operation of a vehicle while non-applicable codes did not help or provide guidance to operations. Additionally, as shown, as small percentage of the code texts were, while applicable, not translatable into the ADS database due to their complex scenarios and language. For the purposes of the proposed conversion methodology in this report, these “not transferable” codes are considered current failures of the conversion process as the method was not able to capture the guidance provided. Figure 6 below shows these percentages.

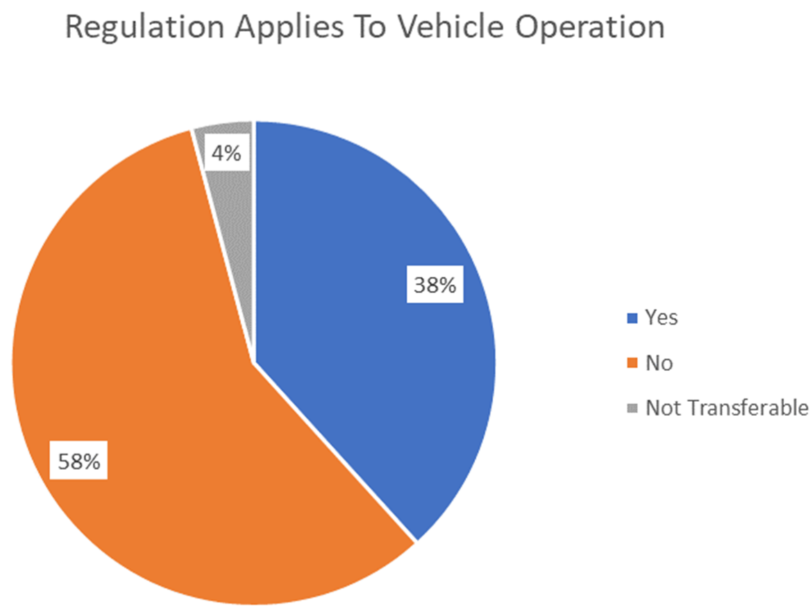


Figure 10 – Regulation Applicability

With 290 total codes reviewed, this "miss" rate of this paper's proposed conversion methodology is promisingly low. Further collaboration on this proposed process with AV designers and ADS engineers could reduce this fraction even further as these groups would have greater insight into real world applications and how ADSs might more easily understand complex codes. Additionally, this classification effort of vehicle codes by applicability removes the need for duplicate effort by future researchers on similar topics pertaining to the operation of vehicles and the California Vehicle Code. That is, future researchers will not need to review a generous portion of the legislative text to determine if their ADS is in compliance. Surprisingly, the majority of codes in the vehicle code book do not relate to vehicle operation but focus more on definitions, fines and penalties, and local authority permissions. This large difference between operationally useful and not could represent an opportunity for future law makers to simplify the vehicle code book, not only for ADS applications, but for standard driving as well.

Priority Key Characteristics

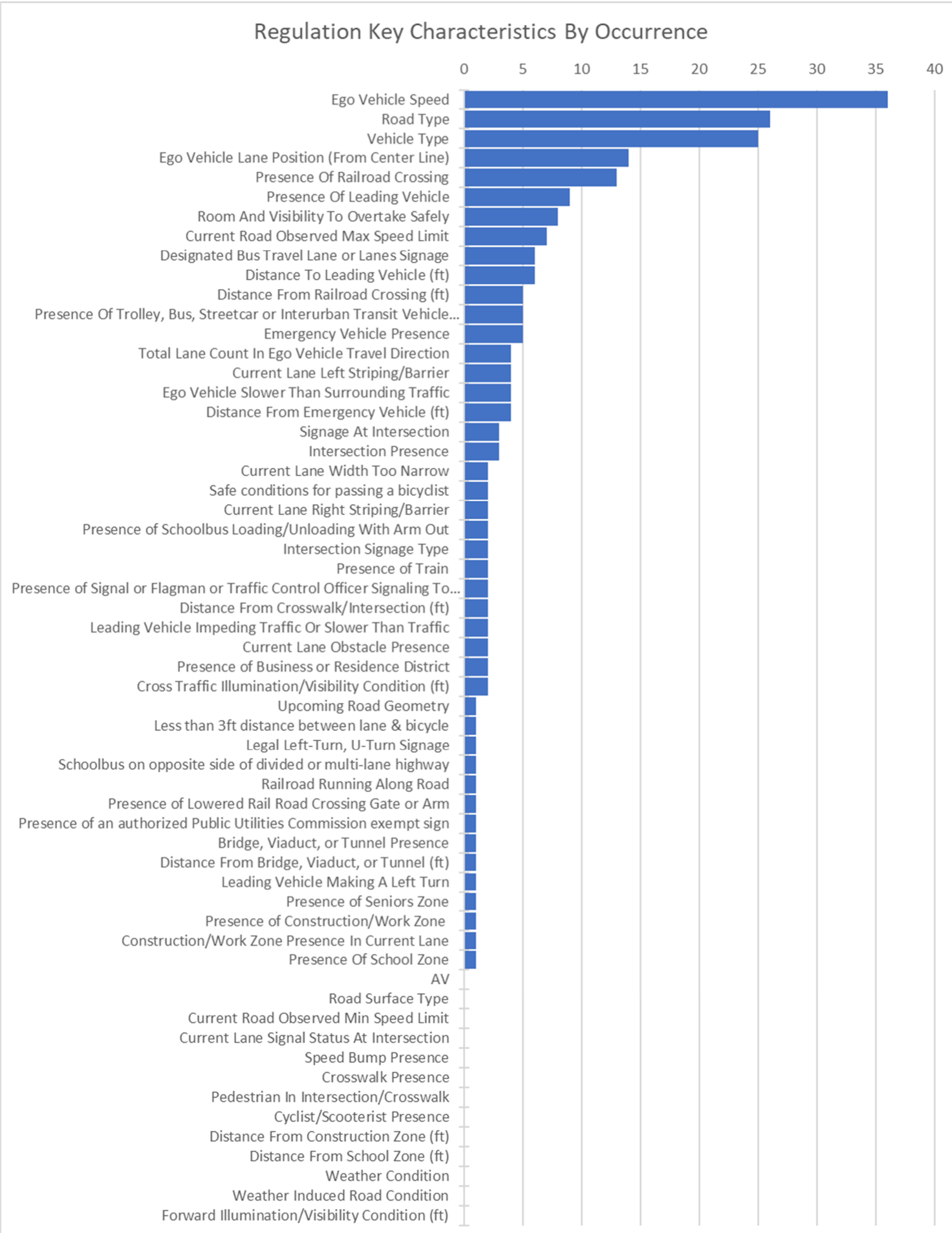


Figure 11 – Regulation Key Characteristics

Next, the vehicle codes focused on some key characteristics more than others. Figure 7 on the previous page shows the occurrence of each key characteristic across all sections studied. Key characteristics of “Ego Vehicle Speed”, “Road Type”, and “Vehicle Type” were referenced in more codes than any other. There is clear legal importance placed on these as they relate to proper vehicle operation.

There are two primary interpretations of this finding. First, codes relating to “Ego Vehicle Speed” should be priorities for ADS designers and AV manufactures. Understandably, many codes include a speed aspect, like regulations regarding school zones, senior zones, work zones, and intersections, to name a few. Understanding and controlling an ADS’ planned speed with regards to its ODD is a must in order for ADSs to maintain legal driving behavior.

Secondly, as ADS technology disseminates into vehicle types beyond just passenger vehicles, these findings show that the traditional ADS focus (by and for passenger vehicle operation) will not be sufficient. Buses have different operating rules than garbage trucks and both should have access to their specific legal rules if they are ever to be developed with ADS technology. Additionally, current ADSs need to be able to distinguish between these different vehicle types to better understand and predict their behaviors. The benefit of an ADS database, like the one proposed in this report, is that these codes and regulations are stored in one place, for access by all road use ADSs.

Vagueness

Level of vagueness was the next focus of review. As shown in figure 9 below, many codes (66%) were classified as having above zero vagueness. About a quarter of all code texts (24%) were classified as high vagueness. These codes (i.e., codes that scored a 2 on the proposed vagueness metric) should be the primary focus for efforts aimed at improving vehicle regulations for ADS operations. Currently, ADSs do not handle vague regulations so much as mimic the way human drivers handle vague regulations. Some simple operational guidelines can and are programmed into an ADS' software but writing this code for every variation of legislation everywhere is time prohibitive. Additionally, programming the rules into an ADS in this way relies on interpretation of these vague codes that will vary by manufacturer and developer. If ADSs are to be better than human drivers, there must be a common, government supported standard for interpreting this large number of vague codes into operational outcomes.

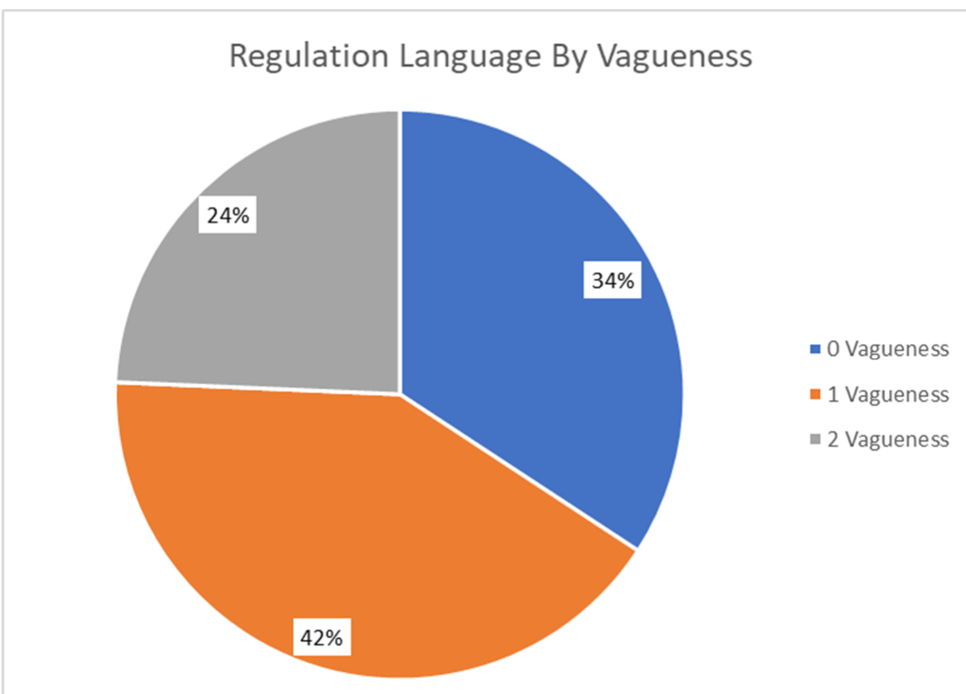


Figure 12 – Regulation Vagueness

Fortunately, the vehicle regulations are not without some specificity. Lawmakers could use the existing zero vagueness codes as a model for improving the high-level vagueness codes. Clearly outlining operating conditions and removing language that references “safe” or “reasonable” could greatly reduce the number of 2 level vagueness. “Safe” and “reasonable” are elements that can be quantified based on vehicle telemetry and operating environment. This effort would pressure legislators and traffic engineers to take a closer look at the specifics of safe driving operation.

Key Characteristics By Vagueness

Breaking down the key characteristics by vagueness level, it is shown in figure 10 on the following page that codes referencing “Room and Visibility To Overtake Safely”, “Ego Vehicle Speed”, and “Ego Vehicle Lane Position” most frequently contained vague language. While vehicle speed appears due to its involvement in many of the codes, the other two are notable for the associated large number of highly vague language. First, many regulations that reference lane position are vague on when specific lanes should be used. For example, if a vehicle is traveling slower than the “normal” speed of traffic, it is illegal to not be in the right most lane, with some exceptions. What constitutes a “normal” speed is vague and left up to interpretation. This value could be quantified as a percentage of surrounding traffic speeds to decrease the vagueness and aid ADSs in their decision making. This approach could also help TMCs and enforcement identify problematic vehicles by standardizing what a slow vehicle is.

Finally, any reference to “Room and Visibility To Overtake Safely” is highly vague and these codes should be the first focus for improving vagueness in the vehicle code book. Again, quantifying the safe “Room” and “Visibility” values in various situation could go a long way towards clarifying the codebook for human operators, ADSs, and other stakeholders.

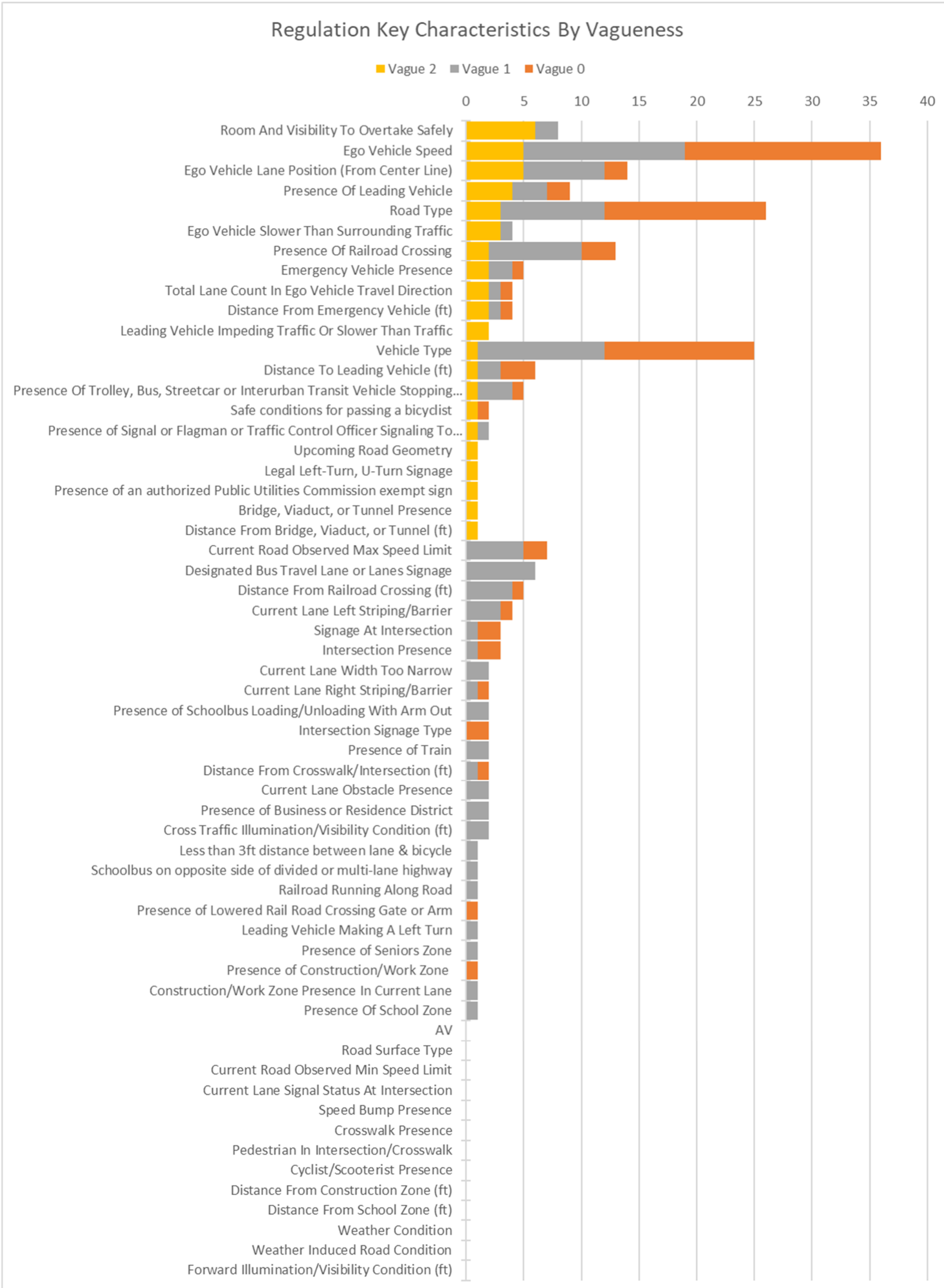


Figure 13 – Regulation Key Characteristics by Vagueness

Planned Scenario Regulation Focus

During the review and conversion process it was observed that legal vehicle operation is often affected by what action an operator is planning to perform. The various "Planned Scenario" characteristics were tracked throughout the conversion process, and some occur more frequently than others. The planned scenario that is most heavily legislated and significantly vague is "Overtaking", as shown in figure 8 below.

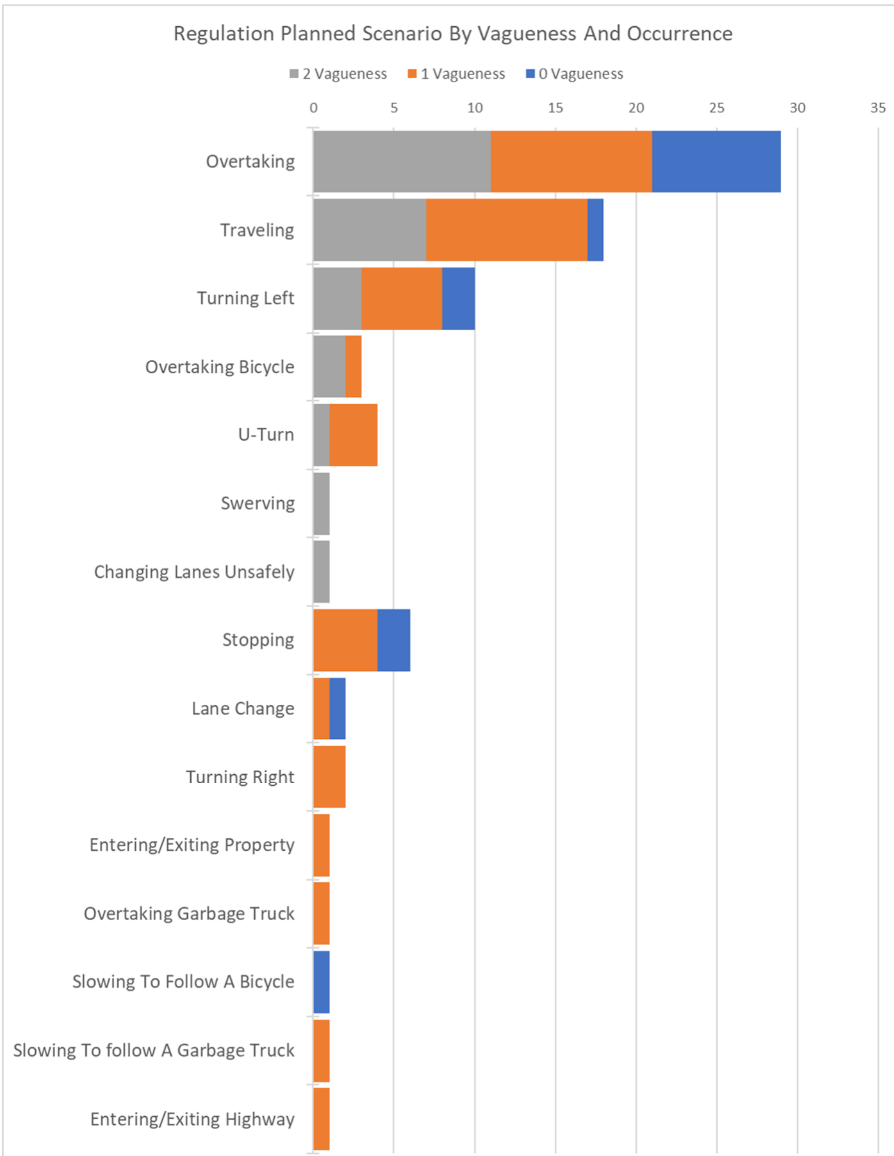


Figure 14 – Regulation Scenario Focuses

Code relating to “Overtaking”, “Traveling”, and “Turning Left” contained the highest level of vague language. Understandably, “Traveling” is common to all codes and so is expected to appear near the top of this list. However, a high number of vague codes pertaining to “Overtaking” is significant due to the action’s high risk and safety concerns. Overtaking is not just an action taken by drivers in a hurry. There are legitimate scenarios where overtaking is necessary for safe and efficient traffic flow, especially when considering the codes requiring vehicles to travel in the right most lane (unless overtaking). Understanding when and how slow leading vehicles can be passed can be difficult for human drivers and ADSs and, while there are the most codes describing the action of overtaking, there is still largely ambiguity on the proper requirements. For example, many “Overtaking” codes allow for overtaking when there is “safe and reasonable space” to do so. This distance is never enumerated, leaving the safety decision up to the vehicle operator.

Simulation Output

As shown in figure 11 below, the ADS equipped simulation vehicle changes its trajectory as its planning module interprets and applies the necessary regulations to its current traveling scenario. The first dotted light green line corresponds to a speed change; the point at which the vehicle recognizes and brakes to slow its advance toward the cyclist. Prior to the next green dotted line, the ADS vehicle consults its trajectory options and decides that the most legal, safe, and efficient path is to overtake the cyclist. Confirming the presence of dotted white lane lines, lack of adjacent vehicles, and complying with all other restrictions, the vehicle then changes lanes, accelerates beyond the cyclist, and returns to its original lane to continue toward its destination.

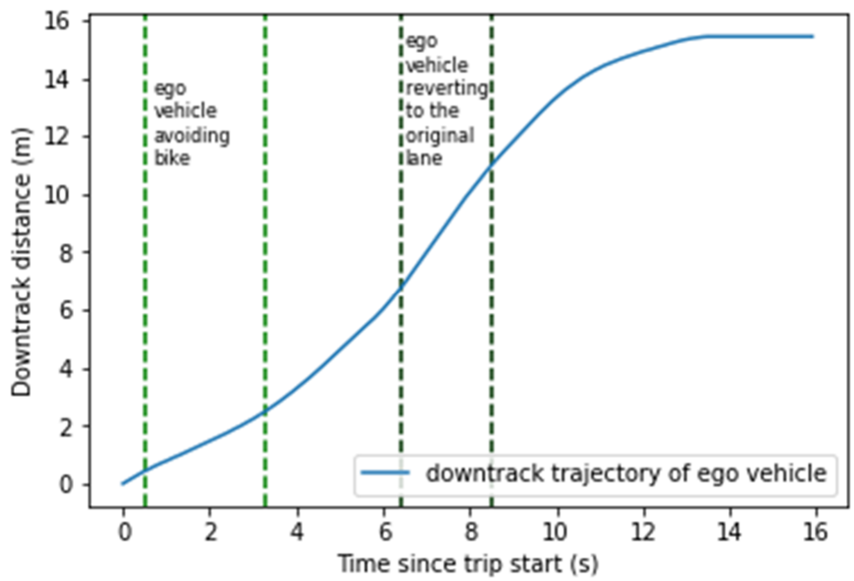


Figure 15 – ADS Vehicle Trajectory During Scenario Simulation

The scenario was developed to include few vague regulations (minimum passing distance for a cyclist is a regulation with a score of 0 for vagueness, other vehicles were removed, etc.) and understandably more simulation and testing with more vague regulations is necessary before on-road testing. However, these results, while simple, indicate a promising method for evaluating existing vehicle regulations and applying them to the real-world vehicle operation by an ADS.

CONCLUSION

As automated driving systems become more advanced, additional data sources, like the driving codebook, will be required to keep the software up to date on the proper driving behaviors of the local jurisdiction. To best provide automated driving systems with these codes, they first must be converted into a machine-readable format. Converting legislative text codes, which contain various levels of vagueness and information, into a standard machine-readable format is non-trivial, and the proposed methodology in this paper serves as a first step in a robust conversion process that could be applied to legislative improvements efforts across all disciplines. Additionally, the process of converting and tabulating these codes has revealed key recommendations for development and improvement of the vehicle codebook at large and simulation testing of this database has demonstrated how process could be implemented in practice.

RECOMMENDATIONS

The codes and regulations governing the operation of vehicles on public roads will need some adaption to better serve planning modules as vehicle operation slowly shifts toward automated driving systems and away from human control. To date, there has not been much discussion on the best forms these codes could take and how they may be converted from legislative text. The development of the legislative conversion methodology proposed in this paper reveals priority areas of code improvement and important observations on the relationship between driving legislation and driving operations. The findings are summarized below.

Restructuring – Vehicle codebooks are currently large lists of texts that are cumbersome to query and reference. Improvements to the codebooks should include updating the format of the codes into a form more easily used by humans and automated driving systems, such as the Key-Value database proposed in this paper.

Priorities – Subsequent regulation aware ADS research and stakeholders of vehicle regulations should focus on codes that pertain to overtaking, vehicle speed, and vehicle lane location. These codes have the highest occurrence and the vaguest language in the selected typical vehicle codebook. A desire to better ADS behavior should necessarily begin with these codes.

Quantification – Measured quantities should be developed and implemented in codes that reference "safe" and "reasonable" operation. For example, specific safety quantification could look like the following: quantifying a minimum gap distance for overtaking and following at certain speeds, defining clear zones at intersections for determining presence of vulnerable road users (VRUs), and/or the quantification of safe speeds for the purposes of road design and speed limits.

Robustness – The vehicle codes apply to a wide range of vehicle types and driving scenarios. To remove duplication and inefficiencies, there should be one source that all automated driving systems can point to for legal reference within the applicable jurisdiction. This single source should be easily updatable and apply for all vehicle types utilizing automated driving systems on public roads.

CONTINUED RESEARCH

The proposed conversion methodology is not just limited to vehicle codes and regulations. The method of converting text rich information into machine-readable databases can be used in various other fields to improve the way governments and municipalities legislate and enforce rules. Other fields that show promise for implementation of a database-based regulation format and integration of automated operating systems include Housing and Zoning Law (e.g. calculation of legal/illegal setbacks, floor area ratios, heights, etc.) and Tax and Revenue Law (e.g. property taxes, assessments, fees, etc.).

The ADS database developed using the methodology proposed in this report will be tested in additional scenarios for validation of its usefulness by fellow researchers within the University of California, Los Angeles' Mobility Lab. This effort aims to demonstrate a working Proof-of-Concept system inclusive of all vehicle regulations in pursuit of table-top and on-road testing. Ideally, in partnership with those efforts, the next evolution in the ADS regulation database will include an automated process, aided by LLMs, for implementing this proposed legislative text-to-database conversion process at scale across all jurisdictions and with every rule of the road.

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