IAM Institute *of* Automated Mobility

Shaping the future of transportation safety, science, and policy

AV Safety Metrics: Evaluation and Calibration based on Naturalistic Driving Data

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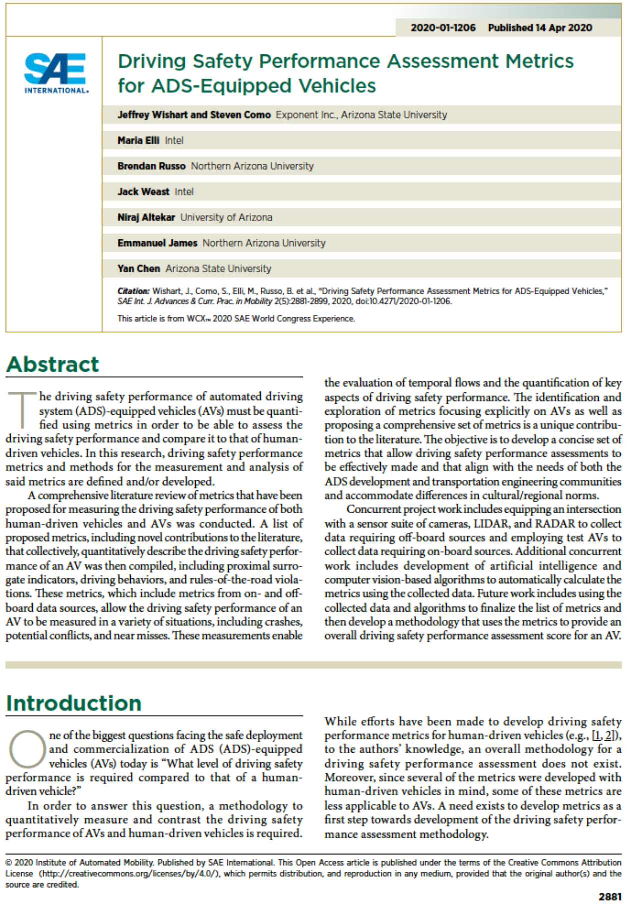
Driving Safety Performance Metrics for ADS

- Institute of Automated Mobility (Arizona):
  - In 2020, proposed a taxonomy and an initial list of Metrics for Safety Assessment of ADS
  - Focused on the assessment of ADS-equipped vehicles safety, but useful in human-driven vehicles also

Black Box Metrics			Grey Box Metrics
Minimum Safe Distance-Related	Universal	Traffic Engineering-Related	
Minimum Safe Distance Violation (MSDV)	Collision Incident (CI)	Time-to-Collision Violation (TTCV)	Human Traffic Control Detection Error Rate (HTCDER)
Proper Response Action (PRA)	Traffic Law Violation (TLV)	Modified Time-to-Collision Violation (MTTCV)	ADS Active (ADSA)
Minimum Safe Distance Factor (MSDF)	Human Traffic Control Violation Rate (HTCVR)	Post-Encroachment Time Violation (PETV)	Achieved Behavioral Competency (ABC)
		Aggressive Driving (AD)	Minimum Safe Distance Calculation Error (MSDCE)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Driving Safety Performance Assessment Metrics for ADS-Equipped Vehicles

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Abstract

The driving safety performance of automated driving system (ADS)-equipped vehicles (AVs) must be quantified using metrics in order to be able to assess the driving safety performance and compare it to that of human-driven vehicles. In this research, driving safety performance metrics and methods for the measurement and analysis of said metrics are defined and/or developed.

A comprehensive literature review of metrics that have been proposed for measuring the driving safety performance of both human-driven vehicles and AVs was conducted. A list of proposed metrics, including novel contributions to the literature, that collectively, quantitatively describe the driving safety performance of an AV was then compiled, including proximal surrogate indicators, driving behaviors, and rules-of-the-road violations. These metrics, which include metrics from on- and off-board data sources, allow the driving safety performance of an AV to be measured in a variety of situations, including crashes, potential conflicts, and near misses. These measurements enable the evaluation of temporal flows and the quantification of key aspects of driving safety performance. The identification and exploration of metrics focusing explicitly on AVs as well as proposing a comprehensive set of metrics is a unique contribution to the literature. The objective is to develop a concise set of metrics that allow driving safety performance assessments to be effectively made and that align with the needs of both the ADS development and transportation engineering communities and accommodate differences in cultural/regional norms.

Concurrent project work includes equipping an intersection with a sensor suite of cameras, LIDAR, and RADAR to collect data requiring off-board sources and employing test AVs to collect data requiring on-board sources. Additional concurrent work includes development of artificial intelligence and computer vision-based algorithms to automatically calculate the metrics using the collected data. Future work includes using the collected data and algorithms to finalize the list of metrics and then develop a methodology that uses the metrics to provide an overall driving safety performance assessment score for an AV.

Introduction

One of the biggest questions facing the safe deployment and commercialization of ADS (ADS)-equipped vehicles (AVs) today is "What level of driving safety performance is required compared to that of a human-driven vehicle?"

In order to answer this question, a methodology to quantitatively measure and contrast the driving safety performance of AVs and human-driven vehicles is required.

While efforts have been made to develop driving safety performance metrics for human-driven vehicles (e.g., [1, 2]), to the authors' knowledge, an overall methodology for a driving safety performance assessment does not exist. Moreover, since several of the metrics were developed with human-driven vehicles in mind, some of these metrics are less applicable to AVs. A need exists to develop metrics as a first step towards development of the driving safety performance assessment methodology.

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https://www.sae.org/publications/technical-papers/content/2020-01-1206/

Purpose of this work

- Develop a methodology for calibration of MSD metric from Naturalistic driving data
- This methodology can help government and regulators set the desired level of risk defined by safety metrics like MSDV derived by real world data

Formulation of Minimum Safe Distance Violation

$$MSDV' = \begin{cases} 1 & if\ d^{lat} < d^{lat}_{min} \wedge d^{long} < \boxed{d^{long}_{min}} \\ 0 & else \end{cases}$$

$$MSDV = \begin{cases} 1 & if\ MSDV' = 1 \wedge\ Originated\ by\ AV \\ 0 & else \end{cases}$$

Where:

d^{long}: longitudinal distance between two vehicles and d^{lat}: lateral distance between two vehicles

d^{long}_{min}: minimum safe longitudinal distance between two vehicles and d^{lat}_{min} : minimum safe lateral distance between two vehicles as defined by RSS model [1]:

$$d^{long}_{min} = \left[v_r\rho + \frac{1}{2}\, a_{max,accel}, \rho^2 + \frac{\left(v_r + \rho a_{max,accel}\right)^2}{2a_{min,decel}} - \frac{v_f^2}{2a_{max,decel}} \right]_+$$

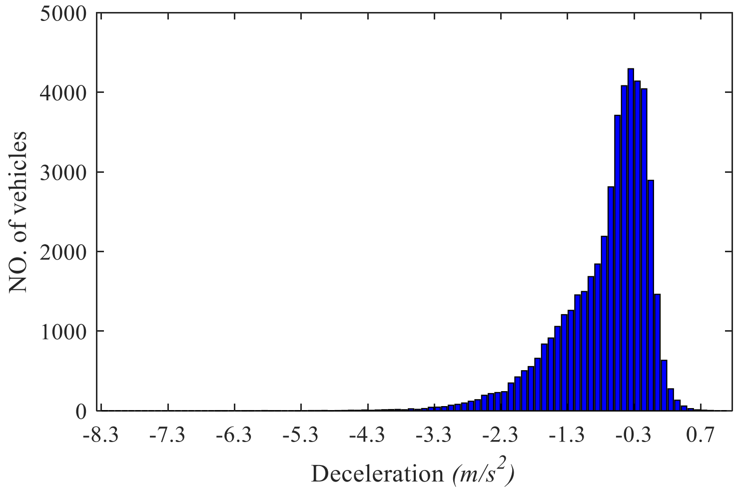
v_r = velocity of the rear car
v_f = velocity of the front car

ρ = response time
$a_{max,accel}$ = maximum acceleration of the rear car
$a_{min,brake}$ = minimum braking of the rear car
$a_{max,brake}$ = maximum braking of the front car

[1] Shai Shalev-Shwartz, Shaked Shammah, Amnon Shashua, "On a Formal Model of Safe and Scalable Self-driving Cars", 2017, https://arxiv.org/abs/1708.06374

Dataset

- LevelXData LA Freeways Dataset (US-based Data): https://www.levelxdata.com/drone-datasets/5-highd-usa.html
  - 3 hours long, 2 different locations in Los Angeles freeways, +30,000 vehicles (car, truck, van, etc)
- Extracted car-following situations:
  - Divided Safe Events (SE) and Safety-Critical Events (SCE)
    - SCE where longitudinal acceleration $\leq -4\ m/s^2$
    - SCE accounted for 0.15% of cases



Calibration Framework

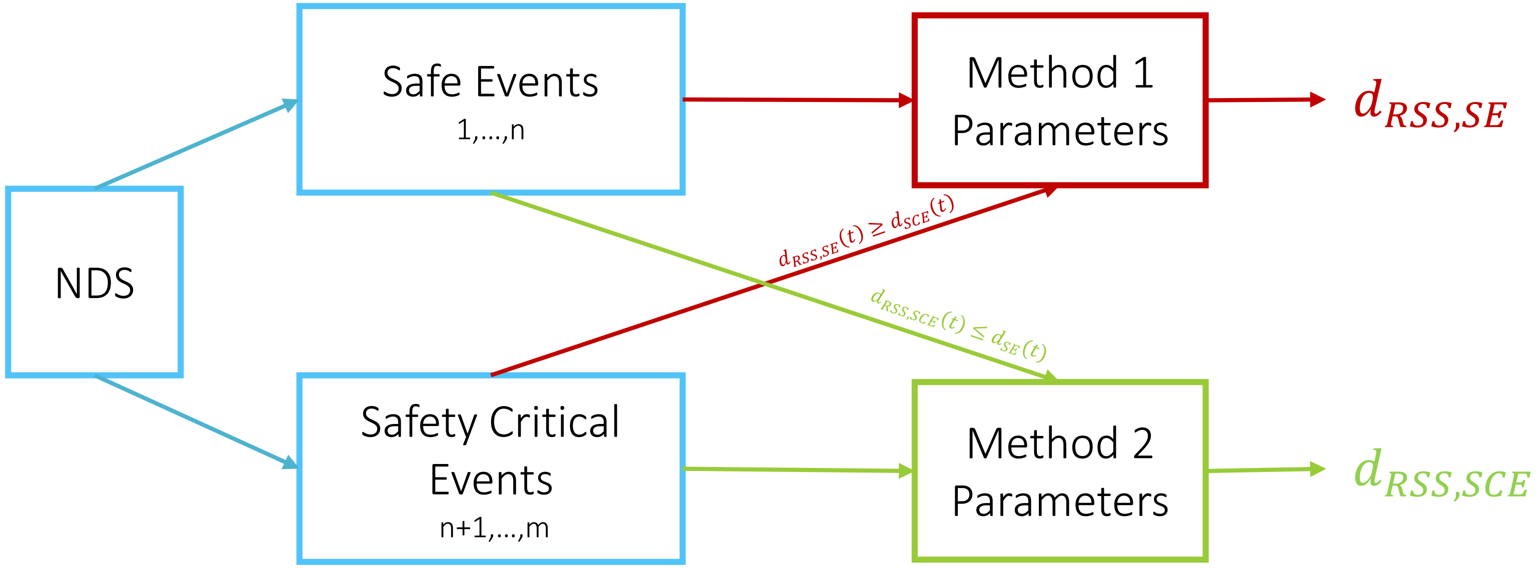
$$\underset{\rho, a_{max,accel}, a_{min,decel}, a_{max,decel}}{\operatorname{argmin}} \sum_{i=1}^{n} \left[\sum_{t_{i0}}^{t_{if}} |d_i(t) - d_{i-RSS}(t)| \right]$$

$$d_{RSS,SE}(t) \geq d_{SCE}(t)$$

$$d_{RSS,SCE}(t) \leq d_{SE}(t)$$

Solved with GA with non-linear constraints

t_{i0}: start frame of vehicle i; t_{if}: end time/frame of vehicle i; $d_i(t)$: headway distance to the preceding vehicle at time t; $d_{i-RSS}(t)$: RSS distance at time t.



Experimental Results

- Parameters' boundaries:

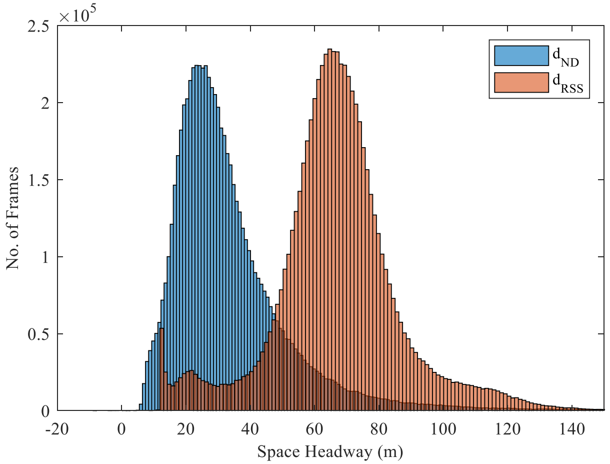
$$\begin{gathered} 0.1s \le \rho \le 2.5s \\ 0.1g \le a_{\max,accel} \le 0.46g \\ 0.1g \le a_{\max,brake} \le 0.82g\ , \\ 0.1g \le a_{\min,brake} \le 0.82g \\ a_{\min,brake} < a_{\max,brake} \end{gathered}$$

- Optimization Results

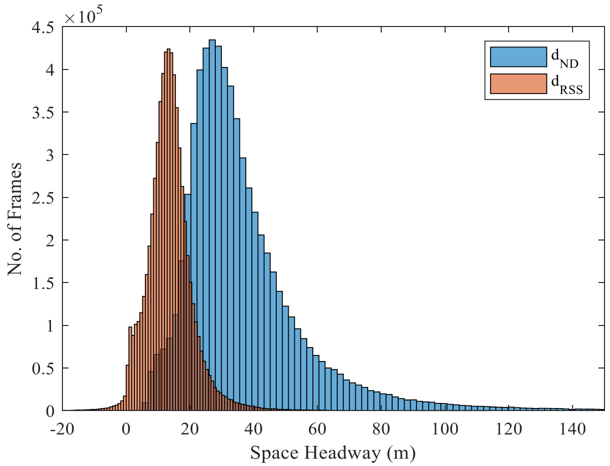
	Method 1	Method 2
$\rho(s)$	1.9236	0.1168
$a_{\max,accel}\left(m/s^2\right)$	3.805	4.836
$a_{\max,brake}\left(m/s^2\right)$	4.585	8.086
$a_{\min,brake}\left(m/s^2\right)$	4.585	7.986
$d_{RSS} \ge d_{ND}$ $[frame\%]$	94.89%	0.0035%
$\overline{d_{RSS} - d_{ND}}(m)$	19.6864	-21.1243
$\sigma(d_{RSS} - d_{ND})(m)$	9.8863	8.4355

Validation of Results

- Validating Method 1 results in complete dataset



Changing ρ= 1.92s to ρ= 0.5s*



*Assumed AV response time

Key Takeaways & Future Work

- Takeaways:
  - Developed a novel methodology to calibrate a safety metric based on Naturalistic driving data without having to focus on safety critical events (rare)
  - Initially validated in US-based data
  - Well calibrated metrics like MSDV can be then used to identify dangerous situations and shape theway we define scenarios for validating AVs

- Future Work:
  - Expand validation with other datasets
  - Expand the validation to other types of driving situations (not only car-following)

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Thank You!

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