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A METHODOLOGY FOR GAUGING USAGE OPPORTUNITIES FOR PARTIALLY AUTOMATED VEHICLES WITH APPLICATION TO PUBLIC TRAVEL SURVEY DATA SETS

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ABSTRACT
Vehicle automation has garnered a significant amount of interest in the recent years. When assessing automated driving (AD) capability of a vehicle, it is important to distinguish between full automation, in which no human driver is required, and partial automation, where a human driver may be required to occasionally intervene and/or take control of the vehicle for portions of the trip. This paper presents a methodology for assessing usage opportunities of partial AD in light-duty vehicle fleets. Key assumptions are: i) The longer the time fraction of driving where AD is active, the better, and ii) drivers will value having longer contiguous sections of AD-active time over having to frequently regain vehicle control. Given second-by-second records of real-world driving trips, the methodology uses a Fuzzy inference system to estimate the fraction of driving time at a certain “quality of use” level. Performing the quality of use assessment for all trips/vehicles in a representative data set can then provide insight to the fraction of population that would likely find partial AD desirable. To demonstrate the proposed methodology, data on vehicle trips from public travel surveys in California (CHTS) and Atlanta (ARCTS) are used along with simplified prototypical models for partial AD. Simulation results are generally in agreement with common perceptions, but show a wide range of possibilities which could be further narrowed down when more detailed trip data becomes available.

Keywords: Partial Vehicle Automation, Real-World Driving, California Household Travel Survey, Atlanta Regional Commission Travel Survey
INTRODUCTION
Automated vehicles are generally defined as those having the capability to perform the critical safety control functions (steering and speed/braking) for at least a portion of the driving time. Different levels of automated driving (AD) have been defined by the National Highway Traffic Safety Administration (NHTSA), ranging from level-0 (No automation) to level-4 (Full self-driving automation) (1). Alternatively, Society of Automotive Engineers (SAE) have their own 5-levels standard (2), with the primary difference according to (3) being that “full automation” (NHTSA level-4) is further broken down into two sub-levels (SAE levels 4 and 5) depending on whether or not the AD system is capable of handling all possible environmental driving conditions. Much interest about full AD (level 4+) has occurred in the media since the announcement by Google in 2012 (4). While commercial availability of full AD is much anticipated in future, level-2 AD features (often termed “partial automation”) are already becoming available in a few high-end vehicle models. Other than a fairly recent safety investigation following a traffic accident fatality in May 2016, in which a partial AD vehicle was involved, partial AD has not had as much media coverage. Barriers to partial AD market penetration could include a push to jump to full AD by some technology developers, as expressed by Google’s self-driving focus and advocacy groups like the National Association of City Transportation Officials (NACTO). NACTO recently released a call to ban partial AD from city streets (and any other non-limited access roadways) due to safety concerns from driver inattentiveness in partial AD scenarios (5). Nonetheless, as many luxury features in high end vehicles eventually trickle down to mass-market vehicles, this research presents a methodology that focuses on gauging the desirability for partial AD among the general populace.

RELATED WORK
Several aspects of envisioned full AD have been studied in the literature. Studies have highlighted issues such as increased safety (6), shared autonomous vehicles (7, 8), various aspects of transportation energy (9-11), as well as holistic system-level energy implications (12-14). On the socio-economic side, studies have attempted to quantify potential business opportunities and/or risks (15, 16), while other studies attempted to gauge attitudes towards AD via public polling (17, 18). Studies that attempt to estimate how long it would take for full AD to become the “new norm” include a range of conjectures between 2030 to 2040 (19, 20).

Only few studies in the literature, such as (14, 21), have attempted to assess the impacts of adoption of partial AD. The authors of (14, 21) attempt to predict changes in transportation energy in four envisioned scenarios; with two scenarios involving “wide-spread” adoption of partial AD (levels 2 and 3) and two scenarios involving full AD. However, the likelihood for each scenario becoming reality was not addressed.

Other than polling for public attitudes towards AD, to the best of the authors’ knowledge, there have been no systematic studies in the literature that attempt to assess the desirability of partial AD via analyzing present-day real-world driving, which is the focus of this research.

SCOPE OF WORK
This paper presents a methodology for gauging the desirability of partial AD apps, focusing on NHTSA/SAE automation level 2, where the driver may relinquish complete control of the vehicle
for certain periods of time, but is required to remain at the steering wheel ready to takeover control when necessary or when prompted by the vehicle. With partial AD being the sole focus of this work, to reduce clutter, further mention of “partial AD” will be replaced by just “AD”. Following software terminology, the term “AD app” is used for describing different regimes where AD could be activated. Since level-2 is partial automation, it is implied that the possibility for activating it is contingent on certain conditions (about the trip/driving) being true, and that there could be different AD apps that can be activated under different driving conditions. Key assumptions for estimating how well an AD app would be valued (from a perspective of increased driver convenience) are:

i) The longer the amount of time (or fraction of total driving time) where the driver can let the vehicle do the driving (i.e. some AD app is engaged), the better.

ii) The longer uninterrupted durations where AD is engaged, the better. For example, if AD could remain engaged without interruptions for 5 minutes, this would be valued higher by a driver, than if AD could remain engaged for five 1-minute durations.

The proposed methodology is first introduced in an abstract sense, where the conditions for an AD app to remain active is some generic function of the instantaneous driving conditions. Trip logs from real-world driving are analyzed for contiguous segments where an AD app remains active, and the length of segment durations is translated to “quality of usage”-levels.

In order to demonstrate the proposed methodology, trip logs from California Household Travel Survey (CHTS) and Atlanta Regional Commission Travel Survey (ARCTS) are analyzed. In preserving, the privacy of survey participants, the public data sets, which are hosted by NREL (22), mask out location-revealing information such as GPS coordinates, altitude and even road type. With second-by-second vehicle speed available, two simplified AD apps are modelled:

1- Highway AD app: which is assumed to be possible to engage as long as the vehicle speed remains above some threshold.

2- Traffic Jam app: which is assumed to be possible to engage as long as the vehicle speed remains below some threshold.

The rest of the manuscript is organized as follows: next section provides detailed explanation of the methodology. The section after, applies the methodology to CHTS and ARCTS data sets. The section that follows, examines the geographic distribution of the sampled vehicles in ARCTS data set. The paper concludes via a summary and discussion of future work.

**METHODOLOGY**

**Abstract Notations**

Data from instrumented vehicles in travel surveys is often arranged (or could be arranged) in the form of a collection of recorded trips $V_{ij}(t)$, where:

- $i$ is an index for the vehicle sample ID (from 1 to $N$)
- $j$ is an index for trips done by vehicle $i$ (from 1 to $m_i$)
$t$ is the time at a certain instant during a trip (between 0 and $T_{ij}$)

$V$ are monitored indicators at every time step of a trip (boldface implies this could be a vector of quantities), such as vehicle speed, type of road, traffic conditions ... etc.

An abstract logic function $\phi_a$ is defined as an indicator of whether or not it is possible to engage an AD app $a$ at time instant $t$ of trip $j$ by vehicle $i$. To reduce reading clutter, indices $i$ and $j$ have been dropped from Eqns. (1-3)

$$\phi_a(t) := \phi_a(V(t)) \in \{True, False\} \quad (1)$$

This allows the calculation of the duration of time $\tau_{ak}$ of an event $k$ where AD app $a$ could have been engaged during the trip and remained active without interruption (i.e. AD available):

$$\tau_{ak} = t_{k_f} - t_{k_s} \mid \phi_a(t) = True \ \forall \ t_{k_s} \leq t \leq t_{k_f} \quad (2)$$

where $t_{k_s}, t_{k_f}$ are respectively the time instances for start and finish of the event $k$ where AD app $a$ could have been engaged.

As previously noted in assumptions, the quality/desirability of an AD event is perceived to get better as the uninterrupted duration of the AD app gets longer. However, setting hard thresholds for how long an event needs to be in order to be “good” is not an easy task. For example, if 5 minutes was set as the threshold, it would make little sense that some person would consider 5 minutes plus one second to be “good” but 5 minutes minus one second “not good enough”. The proposed methodology utilizes Fuzzy sets (23) in order to provide smooth transitions between thresholds.

The equivalent amount of driving time within a trip at some quality level of AD desirability is calculated as:

$$\Omega_{aL} = \sum_k \tau_{ak} M_L(\tau_{ak}) \quad (3)$$

where:

$L$ are Fuzzy sets for quality levels (e.g. “poor”, “good”, “very good”) of an AD app $a$

$k$ is the summation index for all the events where AD app $a$ remained active without interruption during the analyzed trip

$M_L$ is the Fuzzy membership function (value from 0 to 1) for the Fuzzy set $L$

$\Omega_{aL}$ is the total equivalent amount of time at quality level $L$ for AD app $a$ for the analyzed trip

Lastly, by summing up for all the trips recorded for a vehicle sample $i$, one can calculate its fraction of driving time ($\Gamma_{aL|i}$) at different levels of AD quality for each AD app $a$
\[
\Gamma_{aL} = \frac{\sum_{j} \Omega_{aL}y_{ij}}{\sum_{j} T_{ij}}
\]  

(4)

where \(i, j\) are the same indices noted previously for vehicle and trip respectively.

**Special Implementation for Public Travel Survey Data Sets**

The abstract methodology notations discussed in the previous subsection leaves open several specifics such as: what quantities are monitored in the instrumented vehicles, actual logic of the function \(\phi_{a}(V(t))\), number and range limits between Fuzzy membership functions, as well as number and modes of operation for AD apps. This subsection provides a specific implementation of all those details, with the intent of demonstrating the proposed methodology. Key features of CHTS and ARCTS data sets are listed in (Table 1).

**TABLE 1 Features of the Considered Public Survey Data Sets**

| Data Set       | CHTS                          | ARCTS                          |
|----------------|-------------------------------|--------------------------------|
| Data collection period | 2010 to 2012                   | 2011                           |
| Number of instrumented vehicles | 2910                           | 1653                           |
| Vehicle monitoring duration | One week                       | One week                       |
| Geographic range                 | California (whole state)       | Greater Atlanta metro area (20 Counties) |
| Geographic resolution            | Census Tract                   | County                         |
| Samples weighing                  | Rebalanced to Census demographics and income | Rebalanced to Census demographics and income |

As discussed in the scope of work section, due privacy reasons, only the vehicle speed is available in the second-by-second trip records. Despite that, speed could be a reasonable proxy indicator of whether or not certain driving conditions are in effect. Two simplified models of AD apps are studied, where engagement opportunity (Eqn. 1) is defined as only function of speed\(^1\), i.e. \(\phi_{a}(t) := \phi_{a}(V(t))\). The modelled AD apps are:

1- Highway App:

\[
\phi_{Hwy}(t) = \begin{cases} 
\text{True} & \text{if } V(t) \geq V_H \\
\text{False} & \text{otherwise}
\end{cases}
\]  

(5)

\(^1\) Defining AD availability based only on a single parameter, speed, simplifies the exposition of this methodology. However, the authors look forward to refining definitions of AD availability when data sets with additional characterizations of the driving situation and conditions (e.g. visibility, road-type, driver-attentiveness, etc.) become available.
2- Traffic Jam App:

\[
\phi_{\text{Jam}}(t) = \begin{cases} 
    \text{True} & \text{if } V(t) \leq V_f \\
    \text{False} & \text{otherwise}
\end{cases}
\]  

(6)

Four Fuzzy sets \( L \in \{\text{Poor}, \text{Fair}, \text{Good}, \text{Excellent}\} \) with Trapezoidal membership functions (23) are used in this study for quality rating of an opportunity for AD app engagement, as shown in (Figure 1). It is to be noted that the thresholds (values at which Fuzzy sets begin and end) are an initial guess perceived reasonable by the authors, with sensitivity to threshold tuning briefly examined, but full relation to public opinion deferred to future work.

![Fuzzy membership functions for quality rating of opportunity to engage AD.](image)

**FIGURE 1** Fuzzy membership functions for quality rating of opportunity to engage AD.

An illustration of how the methodology is applied to analyze a vehicle sample from a travel survey data set is shown in (Figure 2). Given the speed trace record of some vehicle trip (Figure 2.a), speed thresholds are applied to mark contiguous section of the trip where each AD app could be engaged, as shown in (Figure 2.b). Next, the duration of each contiguous segment is analyzed to calculate an equivalent duration at a quality level. For example, the first segment of the highway app lasted 231 sec (just shy of 4min), which per (Figure 1.a) translates to membership values of 0.57 and 0.43 in the Fuzzy sets ‘Fair’ and ‘good’ respectively (and zero membership in all other sets). The 231 sec duration of this trip segment is then proportionally allocated (133 sec ‘Fair’ and 98 sec ‘Good’) in the book-keeping of AD quality levels (Figure 2.c) for the highway app. Similarly, the second segment of the highway app, which lasted only 10 sec, gets fully allocated to ‘Poor’ quality level (since it had a membership value of 1 in the ‘Poor’ Fuzzy set). Finally, repeating the steps of (Figure 2.a-c) for all recorded trips of a vehicle allows for estimating the net fraction of the vehicle’s driving time at each AD app quality level, as illustrated in (Figure 2.d).
FIGURE 2  Illustration of the steps to calculate fraction of driving time at different AD quality levels.
RESULTS FOR PUBLIC TRAVEL SURVEY DATA SETS

AD cost predictions in the literature (12, 24-26) are often speculative and exhibit quite a bit of uncertainty/disagreement. Without this price information, estimating adoption rates would be very difficult. The results in this study for opportunities to use AD apps are presented as an “indicator” of plausible AD desirability, but should not be interpreted as a statistical expected value (especially since there is a fairly large range uncertainty due to parameter uncertainty and the simplified AD app models. We assume that there exists some threshold for the fraction of driving time at ‘Good’ or ‘Excellent’ quality of AD use, below which, a rational-purchaser/driver would not be interested in the AD app. Conversely, the number of drivers with fraction of driving time above the threshold is indicative that the AD app could be desirable. Since there is presently no data on the desirability limit (which could reasonably vary from one person to another), results presented in this section (Figure 3) are in the form of “Fraction of vehicles population” corresponding to a “Fraction of driving where AD app is good”.

The composite (Figure 3) include 12 sub-plots, where the rows represent the results for an AD app for a public data set, while columns represent examination of the effect of operability limits (speed thresholds in Eqns. 5, 6) listed in Table 2. It may be noteworthy that “more stringent” is the higher speed value for the highway app (i.e. the app will disengage if the speed falls below 45 mph) while the lower speed threshold is more stringent for the traffic jam app. Within each sub-plot, the center-line presents results obtained via setting the thresholds for Fuzzy membership functions to the ones in (Figure 1), while the top and bottom lines (edges of shaded region) represent sensitivity limits for less and more stringent settings of the threshold limits for the ‘good’ Fuzzy set. For less stringent settings, the limits for the ‘good’ Fuzzy set are scaled to 60% of the values in (Figure 1), while the more stringent settings scale it up to 160% of the values in (Figure 1). An example of how to interpret the baseline plot for highway in CHTS data set (center-line in top-middle plot in Figure 3) is that 30% of California vehicles (vertical axis value) may engage the highway AD app at “Good or Excellent” quality level for at least 25% (value from the horizontal axis) of their total driving time.

TABLE 2 Speed Threshold Limits for Operability of AD apps

| Scenario                  | Less Stringent | Baseline | More Stringent |
|---------------------------|----------------|----------|----------------|
| Highway app threshold \(V_H\) (mph) | 35             | 40       | 45             |
| Traffic jam app threshold \(V_J\) (mph) | 20             | 15       | 10             |

Some observations from (Figure 3) include:
- Despite being thousands of miles apart and different region contents (whole state vs one large metro area), the opportunity to engage AD apps seems to have similar trends among CHTS and ARCTS vehicle samples.
- Fraction of vehicles in the population whose drivers could use AD is more sensitive to operability speed threshold in case of the traffic jam app. The sensitivity is less in case of the highway app.
- Fraction of vehicles in the population whose drivers could use the traffic jam app decreases very quickly as the fraction of driving time with good opportunity to engage the app decreases.
increases from 5% to 15% and beyond. Very few vehicles have 30% of their total driving time as a good opportunity to engage the traffic jam app.

- Fraction of vehicles in the population whose drivers could use the highway app decreases steadily as the fraction of driving time increases, but even at the more stringent limits there is a reasonable fraction of the population of the vehicles who could find the app useful.

FIGURE 3 Results of AD app opportune usage analysis for population of vehicles in CHTS and ARCTS data sets.
It is perhaps important to note that the level of mental stress of a driver can vary significantly between different modes of driving (e.g. cruising on the highway or stuck in a traffic jam). As a result, it is necessary to consider that drivers may value different AD apps differently. For example, 10% of total driving time relieved by traffic jam AD app may well be sufficient for a driver to desire it, but insufficient if this is for highway driving. However, it should also be noted that certain conditions that lead to traffic jams (e.g. poor visibility, slippery conditions, road-work) are likely inappropriate for a level-2 AD app to be engaged.

**EFFECT OF GEOGRAPHIC LOCATION**

Public travel survey data sets protect the identity of survey participants by redacting home and work addresses as well as GPS coordinates in trip traces. For researchers benefit however, the data sets provide a rough estimate of home/work location up to some level of geographic resolution. As per (Table 1), the geographic resolution is the census tract-level for CHTS but only county-level for ARCTS. However, with more than 6000 census tracts in California and only 2910 instrumented vehicles in CHTS, an analysis at the census tract level is clearly infeasible. For a county-level analysis, both data sets have a reasonably good number of vehicle samples per county, but when considering samples density (2910 vehicles for all of California compared to 1653 vehicles in greater Atlanta metro area), ARCTS is clearly a geographically denser data set. Furthermore, the counties in ARCTS data set are conveniently surrounding one major urban core (as shown in Figure 4), which allows for easier contrasting between urban core and outlying counties. For these reasons, analysis in the section will only consider AD desirability in the ARCTS data set.

Furthermore, thought there is a fairly wide range of possibilities shown in (Figure 3), only one example case of the parameter settings is considered, with all parameters at the baseline values and considering:

- 10% of driving time for the traffic jam app, which corresponds to ~24% of ARCTS vehicle samples desiring the app
- 25% of driving time for the highway app, which corresponds to ~28% of ARCTS vehicle samples desiring the app

Results for fraction of vehicles desiring each AD app in each county are shown in (Figure 5). A distinctive pattern is observed in (Figure 5), where most “outer ring” counties have higher percentage of vehicles whose drivers would use the highway app. Conversely, most counties close to the urban core have low percentage desirability for the highway app. Such patterns are generally not surprising since highways are often the main commuting corridors in the outlying counties, while areas closer to the urban core generally have more congested traffic (27) and thus fewer opportunities for the highway AD app to remain engaged for long contiguous amounts of time.

Somewhat expectedly as well, areas close to the urban core have relatively high desirability for the traffic jam app; however, these are not the only areas with high desirability. Several of the outer ring counties along major highways leading to the urban core have higher opportunity to use the app. This pattern may imply that frequent traffic jams are not exclusively found in urban centers. There are also some odd-case counties such as Gwinnett and Cherokee, which are outlying counties, but are not very high on desirability for the highway app. Possible explanation for Gwinnett and Cherokee may be that those two counties have high within-county job growth and thus a relatively lower fraction of commuting outside the county (28).
FIGURE 4 County layout in ARCTS data set.

FIGURE 5 Percentage of ARCTS county vehicles that could find AD apps desirable

CONCLUSIONS
A methodology for estimating usage opportunity of partial automated driving in light-duty vehicle fleets was presented. The methodology utilizes Fuzzy sets to assess quality levels of driver convenience (assuming longer contiguous time segments with an AD app engaged are better) and fraction of total driving time where an AD app is in good use (i.e. high AD availability). Real-world driving trip data from the public travel surveys CHTS and ARCTS was used to demonstrate the proposed methodology. With a limitation that public travel surveys only provide speed of the vehicle, two simplified prototypical AD app models were constructed in order to assess opportunity to use partial AD in high and low speed regimes. Sensitivity analysis was conducted for: i) tuning parameters of the fuzzy membership functions, ii) speed thresholds for range of operation of the AD apps, and iii) fraction of drive time at “good” quality of use. ARCTS data set was also used to examine the effect of geographic variation (urban core vs outer suburbs). Simulation results agree with common perceptions such as urban core areas seeing more of traffic jam conditions, and outer suburbs seeing more highway-like driving. However, simulation results
(and sensitivities) show a wide range of possibilities for fraction of the population that could find partial AD desirable. Narrowing down the range of estimates would be pursued in future work through three thrust efforts: i) Public polling for how long a “time duration of hands off the wheel” would be considered good, ii) Public polling for how much fraction of driving time relieved by AD would make it desirable, and iii) Collection of better-quality data sets on real-world driving that would allow more detailed models of partial AD apps to be simulated.

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