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Exploring causes and effects of automated vehicle disengagement using statistical modeling and classification tree based on field test data

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ABSTRACT

Automated vehicles (AV) testing on the public roads is ongoing in several states in the US as well as in Europe and Asia. As long as the automated vehicle technology has not achieved full automation (Level 5), human drivers are still expected to take over the steering wheel and throttles when there is an automated vehicle disengagement. However, contributing factors and the mechanism about automated vehicle-initiated disengagement has not been quantitatively and comprehensively explored and investigated due to the lack of field test data. Besides, understanding human drivers' perception and promptness of reaction to the AV disengagement is essential to ensure safety transition between automated and manual driving. By harnessing California's Autonomous Vehicle Disengagement Report Database, which includes the AV disengagement data from field tests in 2016–2017, this paper quantitatively investigated the AV disengagement using multiple statistical modeling approaches that involve statistical modeling and classification tree. Specifically, the paper identifies the contributing factors impacting human drivers' promptness to AV disengagements, and quantitatively investigates the underlying causes to AV disengagements. Results indicate that current AV disengagement on public roads is dominated by causes due to a planning issue. The cause of an AV disengagement is significantly induced by lacking certain numbers of radar and LiDAR sensors installed on the automated vehicles. These thresholds of these sensors needed are revealed. Cause of disengagement and roadway characteristics significantly impact drivers' take-over time when facing an AV disengagement. AV perception or control issue-based disengagement can significantly extend drivers' perception-reaction time to take over the driving. The quantitative knowledge obtained ultimately facilitates revealing the mechanisms of the automated vehicle disengagements to ensure safe AV operations on public roads.

1. Introduction

Although automated vehicles (AV) are designed with targets to improving highway safety, when testing automated vehicles on public roads, issues related to safety has continuously been a concern to the general public, government agencies, as well as auto manufacturers. The Society of Automotive Engineers (SAE, 2018) defines six levels of driving automation from Level 0 (No Driving Automation) to Level 5 (Full Driving Automation). In the definition of levels of driving automation given by SAE, the vehicle that operates under either Level 3 or Level 4 driving automation can drive itself with required conditions, which are associated with speed, geography, roadway, environment, and traffic. The major difference between Level 3 and Level 4 driving automation is that Level 3 driving automation does not require the human driver to drive with this level of driving automation engaged unless the vehicle requests that the human driver take over the driving task if needed. Level 4 driving automation will not request that the human driver take over the driving task with this level of driving automation engaged. The vehicle will automatically pull over in case the required conditions are not met.

Although auto manufacturers are expecting to launch Level 5 AV (without a steering wheel) before 2020, it will probably take additional five to ten years to make vehicles operating under Level 5 driving automation available in the market (O'Kane, 2018; Hawkins, 2018). Therefore, human drivers are still needed since these AVs on public roads are most likely under Level 3 (Conditional Driving Automation) or Level 4 (High Driving Automation) in the coming decade.

The shift of vehicle control from automated driving to manual driving is defined as automated vehicle disengagement. For example, California Department of Transportation defines AV disengagement as "a deactivation of the autonomous mode when a failure of the autonomous technology is detected or when the safe operation of the vehicle

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requires that the autonomous vehicle test driver disengage the autonomous mode and take immediate manual control of the vehicle (California Department of Motor Vehicles (CA DMV, 2016)." The definition given by CA DMV clearly indicates that the AV disengagements can only be initiated by the vehicle that operates under Level 3 or Level 4 driving automation. Therefore, human driver-initiated disengagements are not discussed in this paper.

From the safety perspective, it is essential to understand the interaction between automated driving and human drivers. In fact, existing public road AV test crash data shows that crashes happened with AV disengagement issues involved, particularly some of the crashes have resulted in fatalities involving either automated vehicle drivers or pedestrians (Fleming, 2016; Green, 2018; Wakabayashi, 2018). Both the U.S. National Highway Traffic Safety Administration (NHTSA) and the National Transportation Safety Board (NTSB) investigated fatal crashes onsite and published either preliminary or final reports. According to these reports, failing to respond to take-over requests in time is the major reason that results in these fatal crashes (DOT-National Highway Traffic Safety Administration (NHTSA, 2016; NTSB, 2018a,b). Although identified as a major reason, what factors impact driver's take-over time and how large the impact still remains unknown. From the perspective of preventing potential safety issues caused by AV disengagement, what the major causes that lead to AV disengagement are needed to be investigated quantitatively. With these research questions, a comprehensive and quantitative investigation of automated vehicle disengagement causes and effects is imperatively needed to understand the mechanism of AV disengagement so as to facilitate the prevention of future crashes caused by AV disengagement.

In practice, this type of effort is refrained mostly due to the lack of sufficient disengagement data/information caused by:

1 Some of the automated vehicle field tests are still underway in the closed course without field test data being published;
2 For public road tests, most states' Department of Motor Vehicles (DMV) did not require AV manufacturers to submit the disengagement report with information regarding what the reasons that induced the disengagements are, and how long it took the human driver to react to the take-over request.

Starting 2016, California DMV (CA DMV) has begun to require every manufacturer authorized to test automated vehicle on public roads to submit an annual report summarizing the AV disengagements during testing (CA DMV, 2018). All the disengagements reports were made available to the public, which offers potential to further investigate into AV disengagement. The only related study at this moment is that Favarò et al. (2018) examined California's AV disengagement reports by providing an overview of automated vehicle disengagements and analyzing triggers of them. That research is very meaningful for creating the digital database as well as providing an elaborate analysis of trends and specific contributions per manufacturer. At the same time, that research is more of a qualitative study. Significant factors contributing to human drivers' take-over time as well as reasons that caused AV disengagements has not been quantitatively studied and therefore, still remain unknown.

Therefore, the objective of this paper is to quantitatively explore the AV disengagement mechanism by understanding its patterns, causes, and effects on driver's perception-reaction time for take-over requests in a quantitative manner based on the most recent records from the California AV disengagement database. The relationship among the causes of AV disengagement, time, and vehicle sensors, as well as the relationship among the driver take-over time, roadway environment, and disengagement causes are to be explored and quantified using multiple modeling approaches that involve statistical modeling and classification tree.

2. Literature Review

2.1. Current practice: understanding the causes of AV disengagements

Given the definition of automated vehicle disengagement by CA DMV, an automated vehicle requests a human driver to take over driving under two circumstances: (a) there is a technical issue from the automated driving system that is installed on the vehicle, or (b) the human driver is not confident with the interaction between automated vehicle and driving environment, due to which the driver regains the control of driving without being notified by the automated vehicle to do so. Pendleton et al. (2017) introduce that a typical automated driving system consists of two major parts, which are hardware system and software system. Therefore, various reasons from either hardware or software system may cause disengagement of the automated driving system.

Researchers have started to explore the causes of AV disengagement. Dixit et al. (2016) identified the sources of AV disengagement using the reports collected by CA DMV. They categorize six reasons for disengagement, which are weather, construction zones, road infrastructure, driver-initiated, system failure, and other road users. Favarò et al. (2018) define the causes into four "macro-categories", which are human factors, system failure, external conditions, and others. Both of them did a thorough exploration of the disengagement reports.

In summary, most of these findings are qualitative and focused on identifying environmental causes. None of both research efforts either investigated the cause of disengagements from the AV technology and operations perspectives, or quantitatively identified the contributing factors to AV disengagement Mechanism and contributing factors to their defined cause of disengagement still remain unexplored.

2.2. Current practice: the behavioral adaptation of AV technology

Despite AVs have the potential to impact safety significantly by reducing crashes caused by human errors (e.g., impaired driving or distracted driving), it might still take some time for the general public to adjust to the new technology. The reason can be explained by the concept of "behavioral adaptation", which refers to the fact that human drivers need to make a few changes in response to the AV technology. These changes may come from traffic and transport psychology (Rudin-Brown and Jamson, 2013).

In the past few years, studies regarding the investigation of the behavioral adaptation of the AV technology have been conducted via either the driving simulation study or the survey study. Buckley et al. (2018) conducted a qualitative study to examine drivers' responses to the Level 3 driving automation via a driving simulator study. They conclude that the trust of AV technology consists of ability, helpfulness, and integrity. Robertson et al. (2017) investigated how Canadian drivers would adapt their behaviors if using vehicles operating with Level 3 driving automation via a survey study. The conclusions claim that many drivers believe that they would not need to pay attention to the road environment when using Level 3 driving automation, and some of them would modify their driving behaviors in a way that would undermine the safety objectives. Hulse et al. (2018) conducted an online survey with regards to the safety and acceptance of AVs. They found that gender, age, and risk-taking had varied relationships with the general attitudes about AVs.

2.3. Current practice: driver taking over time (TOT)

As it is difficult to have Level 5 AV widely deployed in the near future, human drivers are still expected to take over the driving when requested by the automated driving system in Levels 3 and 4 system.

Studies regarding the AV-related driving behavior show that human drivers are likely to engage themselves in the non-driving tasks while driving an automated vehicle (Merat et al., 2014; Jamson et al., 2013). These non-driving tasks shift drivers' attention away from the traffic, occupy their working memory, and result in a loss of situation awareness (Baumann et al., 2007; De Winter et al., 2014; Heikoop et al., 2018). If the driver is engaged with some non-driving tasks while the automated vehicle requests him/her to take over, he/she has to reallocate the attention to the driving environment, regain situation awareness, and then take over the driving tasks (Körber et al., 2016).

To ensure the transition from automated driving to manual driving safely, it is essential that human drivers can react to the take-over request and control the vehicle in an appropriate and timely manner. Human driver's response to a take-over request has been investigated through several studies. Schwarz et al. (2016) found that reaction time and performance measures showed that there was a 15- to the 25-s period between the physical takeover and a return to normal driving performance. Payre et al. (2016) conducted a driving simulator study in examining manual control recovery under emergency. They found that a higher degree of trust in automated driving meant a longer reaction time when manual driving is necessary. Zeeb et al. (2015) used a driving simulator to explore how drivers' allocation of visual attention during highly automated driving influences driver's take-over. They found that primary cognitive determines the take-over time; high-risk drivers reacted late and inappropriately in the take-over situation. Trick et al. (2010) indicate that high traffic density prolongs the take-over time and further increases the standard deviation of lane position.

In summary, the current practice on driver's take-over time is mostly focused on analyzing the impact of the driving environment. There is a lack of investigation into the take-over time mechanism as related to how the automated driving system works in an AV, which requires further quantitative investigation.

3. Methodology

3.1. Data collection

The disengagement data can be retrieved from the CA DMV's Autonomous Vehicle Disengagement Report Database (CA DMV, 2018). Starting in 2016, the California Autonomous Vehicle Testing Regulations require every manufacturer to test automated vehicles on public roads to submit an annual report summarizing the disengagements records during testing.

The CA DMV's Autonomous Vehicle Disengagement Report Database allows users to download all submitted disengagement reports. Then users can convert them into the digital database on their own. In this study, the most recent disengagement data that can be obtained is from August 2016 to November 2017, which is also the latest published data by CA DMV.

In this study, the following information from the disengagement reports is retrieved and then formatted into the disengagement database of this study: manufacturer's name; the reason why disengagement happened; the location of where disengagement happened; and time needed for human drivers to take over when disengagement happened.

In addition to the data retrieved from the submitted disengagement reports, the levels of their driving automation as well as the numbers of sensors installed on each manufacturer's testing AVs are included in the database. The data was collected based on the descriptions in the reports.

In the analysis, we considered that the number of sensors for each sensor type is consistent with the sensor detection coverage. To justify this, it is necessary to understand the sensors that are installed on the AV, which are typically LiDAR sensors, radar sensors, and cameras.

LiDAR sensors refer to a light detection and ranging device, which is the key component for detecting objects on the road (Pendleton et al., 2017). Although one LiDAR sensor can provide 360-degree coverage, only one spinning LiDAR on top of the vehicle can be insufficient to detect obstacles moving in fast speeds in some cases (Felix, 2019). Therefore, many AV manufacturers, such as General Motors and Waymo, choose to install multiple LiDAR sensors on their AVs instead of only one to enhance the LiDAR's accurate detection coverage.

Radar sensors have longer detection range than LiDAR sensors. However, radar sensors have their own limitation that they can detect vehicles more accurately than pedestrians due to its reflectivity issue (Fleming, 2012; Hussain and Zeadally, 2018). Each radar sensor has its own detection coverage with being most accurate in a detection cone of 30°. AV manufacturers apply multiple radar sensors at different positions of the vehicle to increase the coverage of the detection range.

Cameras have the advantage of detecting lane markings and recognizing traffic signs as well as signals (Wei et al., 2013). However, the recognition accuracy is not as good as either LiDAR sensors or radar sensors. The images provided by cameras are subject to view angle and lens distortion which needs to be corrected before processing (Wei et al., 2013). Thus, Felix (2019) believes that the correction of lens distortion would remove parts of the image and consequently reduce the coverages of cameras. Therefore, AV manufacturers install multiple cameras with lens that can result in less distortion at multiple positions of the AV to address the distortion and increase the view angle, so that accurate view coverage will be increased.

Based on the discussion above, it indicates that sensor detection coverage is consistent with the number of this type of sensors used on AV. And this statement is true for camera, radar and LiDAR sensors. Therefore, we used the number of each sensor as independent variable to represent the sensor detection coverage in the analysis.

A total of 503 valid disengagement records were eventually included in this study. This is by far the most completed automated vehicle disengagement database, which we can identify and collect from all possible sources. Fig. 1 illustrates a sample of the processed AV disengagement data including number of sensors for each sensor type, cause of disengagement, and take-over time.

3.2. Variables

3.2.1. Safety performance measures

Cause of disengagement

The definition of AV disengagements is meaningful because it indicates that disengagements can be initiated either by the automated driving system or by the vehicle itself.

The automated vehicle-initiated disengagements reflect the limitation of the automated driving systems. Pendleton et al. (2017) conducted a thorough investigation into the technology of automated vehicles. They also brought up that there are two essential components, hardware sensors and software computational platform, which are included in a typical automated vehicle. In addition, they indicate that the core competencies of an automated vehicle software system can be categorized into three phases, perception, planning, and control. The sequence of the phases is consistent with the reality of how an automated vehicle operates on the road. These phases start with sensing the driving environment (perception), then making decisions (planning), and eventually driving the vehicle itself (control).

Per the automated vehicle disengagement reports submitted by manufacturers, each cause of disengagement record was described using simple sentences. For example, Delphi Automotive System (2017) described the cause of disengagement with "poor lane markings", "traffic light detection", "pedestrian traffic" and so forth. Waymo (2017) defines the cause of disengagement with "Disengage for a perception discrepancy", "Disengage for incorrect behavior prediction of other traffic participants" and so forth.

Since CA DMV clearly defines the AV disengagement, which is either due to the automated driving system or the vehicle itself, the AV disengagement report submitted by each AV manufacturer does not include those transitions from automated to manual driving initiated by human drivers themselves without being requested to do so. Therefore,

ID	Manufacturer	Month/Year	SAE Levels	Lidars_N	Radars_N	Cameras_N	Location	Cause of Disengagement	Take-Over Time
1	A	04/17	Level_3	9	10	2	Street	Heavy pedestrian traffic	<=0.5 seconds
2	A	04/17	Level_3	9	10	2	Street	Heavy pedestrian traffic	<=0.5 seconds
3	A	04/17	Level_3	9	10	2	Street	Heavy pedestrian traffic	<=0.5 seconds
4	A	04/17	Level_3	9	10	2	Street	Heavy pedestrian traffic	<=0.5 seconds
5	A	05/17	Level_3	9	10	2	Street	Heavy pedestrian traffic	<=0.5 seconds
6	A	05/17	Level_3	9	10	2	Street	Heavy pedestrian traffic	<=0.5 seconds
7	A	05/17	Level_3	9	10	2	Street	Cyclist	<=0.5 seconds
8	A	05/17	Level_3	9	10	2	Street	Traffic light detection	<=0.5 seconds
9	A	05/17	Level_3	9	10	2	Street	Construction	<=0.5 seconds
10	A	05/17	Level_3	9	10	2	Street	Construction	<=0.5 seconds
11	A	05/17	Level_3	9	10	2	Street	Construction	<=0.5 seconds
12	A	05/17	Level_3	9	10	2	Street	Construction	<=0.5 seconds
13	A	05/17	Level_3	9	10	2	Interstate	Localization divergence	<=0.5 seconds
14	A	05/17	Level_3	9	10	2	Interstate	Traffic light detection	> 0.5 seconds
15	A	05/17	Level_3	9	10	2	Interstate	Poor lane markings	> 0.5 seconds
16	A	05/17	Level_3	9	10	2	Interstate	Poor lane markings	> 0.5 seconds
17	A	05/17	Level_3	9	10	2	Street	Pedestrian traffic	> 0.5 seconds
18	A	05/17	Level_3	9	10	2	Street	Cyclist	> 0.5 seconds
19	A	05/17	Level_3	9	10	2	Street	Pedestrian traffic	> 0.5 seconds
20	A	05/17	Level_3	9	10	2	Street	Pedestrian traffic	<=0.5 seconds
21	A	06/17	Level_3	9	10	2	street	Heavy pedestrian traffic	<=0.5 seconds
22	A	06/17	Level_3	9	10	2	street	Heavy pedestrian traffic	<=0.5 seconds
23	A	06/17	Level_3	9	10	2	street	Heavy pedestrian traffic	<=0.5 seconds
24	A	06/17	Level_3	9	10	2	street	Vehicle cut in	<=0.5 seconds
25	A	06/17	Level_3	9	10	2	street	Vehicle cut in	<=0.5 seconds
26	A	06/17	Level_3	9	10	2	street	Construction	<=0.5 seconds
27	A	06/17	Level_3	9	10	2	street	Construction	<=0.5 seconds
28	A	06/17	Level_3	9	10	2	street	Pedestrian traffic	<=0.5 seconds
29	A	06/17	Level_3	9	10	2	street	Pedestrian traffic	<=0.5 seconds
30	A	06/17	Level_3	9	10	2	street	cyclist	<=0.5 seconds

Fig. 1. Processed CA AV Disengagement data.
*Note that "A" is used for representing the original name of the AV manufacturer.

referring to the classification, there are 3 categories of the causes of disengagements defined in this paper. Table 1 summarizes the detailed explanation of each cause of disengagement.

Time needed for taking over (Take-Over Time)

CA DMV requires every company testing automated vehicle on public roads to collect the "period of time elapsed from the autonomous vehicle test driver was alerted of the technical failure and the driver assumed manual control of the vehicle" in their annual disengagement reports. Based on the definition, the time can be measured only when an automated vehicle-initiated disengagement occurred.

The Take-Over time (TOT) can be accurately collected if the driver's assuming manual control of the vehicle can be clearly defined. disengagement reports that were retrieved into the database of this manuscript. It turned out that all AV manufacturers did not specifically mention how drivers assume manual control in their reports. As California DMV adopted the definition of driving automation from the Society of Automotive Engineers (SAE), therefore, we then referred to the official document entitled "Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles" (SAE J3016) and found out the definition of assuming manual control of the vehicle.

According to the description in SAE J3016, the human driver must perform the driving tasks requested by the automated driving system if the disengagement happens, which includes and not limited to lateral vehicle control via steering or longitudinal vehicle control via acceleration/deceleration. To conclude, how driver assumed manual control of the vehicle is depending upon the requests by the AV, which can be the action of hands back to the steering wheel or feet back on the pedal or both.

Per many auto manufacturers, they claim that their test drivers disengaged the automated vehicle and took control of the vehicle immediately. In this case, they used "N/A" to reflect to the take-over time.

Table 1
Classification of Cause of Disengagement.

Cause of Disengagement	Definition	Examples
Perception Issue	An issue of hardware sensors (i.e., LiDAR, Radar), environmental perception or localization during perception phase that requires a human driver to take control of driving.	1 "Hardware discrepancy" (Zoox Inc, 2017); 2 "Traffic light detection" (Delphi Automotive System, 2017); 3 "Localization error" (Drive.ai, 2017)
Planning Issue	A planning issue of making decisions (i.e., stop/go, accelerate/decelerate, change lanes) during the planning phase that requires a human driver to take control of driving.	1 "Disengage for a recklessly behaving road user" (Waymo, 2017); 2 "Undesired motion planning behavior" (Drive.ai, 2017)
Control Issue	A controlling issue from either automated driving system or the vehicle itself during control phase that requires a human driver to take control of driving.	1 "Steer control profile undesirable" (Baidu, 2017); 2 "AV is about to rear-end another vehicle due to insufficient deceleration of the AV" (Nissan, 2017)

Table 2
AV Disengagement Data Variables.

	Variable	Description	Type	Definition	Count (Proportion)
Performance/Dependent Variable	Cause of Disengagement	Different causes of disengagement	Categorical	1 = Perception issue 2 = Planning issue 3 = Control issue	164 (33%) 301 (60%) 38 (7%)
	Time needed for taking over (Take-Over Time)	Different levels of time needed to respond to a take-over request (TOT)	Ordinal	1 represents above 0.5 seconds 0 represents within 0.5 seconds	81 (16%) 422 (84%)
Explanatory Variables (Potential Contributing Factors)	SAE Levels	The automated driving system installed on testing automated vehicles	Categorical	1 = SAE Level 3 2 = SAE Level 4	336 (67%) 167 (33%)
	Number of LiDAR Sensors	The number of LiDAR sensors installed on testing automated vehicles.	Numerical/ Categorical	1 represents 5 or fewer LiDAR sensors 2 represents 6 or more LiDAR sensors	309 (61%) 194 (39%)
	Number of Radar Sensors	The number of radar sensors installed on testing automated vehicles.	Numerical/ Categorical	1 represents 9 or fewer radar sensors 2 represents 10 or more radar sensors	320 (64%) 183 (36%)
	Number of Camera Sensors	The number of camera sensors installed on testing automated vehicles.	Numerical/ Categorical	1 represents 7 or fewer camera sensors 2 represents 8 or more camera sensors	273 (54%) 230 (46%)
	Roadway Characteristic	If the disengagement occurred when driving on local roads	Binary	1 = Local roads; 0 = Freeway/Interstate Highway etc.	428 (85%) 75 (15%)

Gold et al. (2013) indicate a range of 0.41–0.54 s of gaze reaction time for receiving the take-over request in the study. Therefore, for further analysis, "0.5 s" is applied as a threshold to classify two levels of Taking-Over Time (TOT). Those cases that the test drivers took immediate control of the vehicle are considered as taking over the driving within 0.5 s. The rest of cases are considered as taking over the driving using above 0.5 s. Eq. (1) summarizes the categories for TOT.

$$TOT_i = \begin{cases} TOT_i \leq 0.5 \quad seconds \\ TOT_i \; > 0.5\, seconds \end{cases} \tag{1}$$

3.2.2. Potential contributing factors

How the automation levels, number of hardware sensors (LiDAR, radar, and cameras) installed on testing automated vehicles, and roadway characteristics affect the cause of disengagement and Take-Over Time (TOT) are of interests in this research. These factors are included as explanatory variables in the models of the cause of disengagement and TOT. Detailed descriptions of the factors are summarized in Table 2.

Upon the completion of the data preparation, software package SPSS 16.0 is used to perform the ordinal logistic regression, where the numbers of LiDAR, radar, and camera sensors are particularly used as categorical independent variables. These variables are categorized based on mean values. Furthermore, decision trees models are developed using a package named "rpart" in R studio. In this case, a number of LiDAR, radar, and camera sensors are used as numerical independent variables. The reason why choosing "rpart" to build these decision tree models is due to the function of cross-validation (Westreich et al., 2010), which the training and testing datasets are the same for saving the disadvantage of small sample size.

3.3. Modeling approaches

3.3.1. Ordinal logistic regression

The AV disengagement can occur due to a perception, planning, or control issue of the automated driving system, as shown in Table 1. The causes of disengagement have a meaningful order if following the process of how an AV is operating on the road, which the AV percepts the driving environment using hardware sensors, then makes decisions, and finally drives itself. Therefore, the ordinal logistic regression model can be used for analyzing the causes of disengagement as a function of multiple related factors from Table 2. The equations can be expressed by the following:

$$P(cause \quad of \quad disengagement = i) = \frac{1}{(1 + e^{-z_i})} \tag{2}$$

$$z_i = a_i + \sum_k \beta_k x_{ik} \tag{3}$$

Where,

$P_i(cause\ i\ of\ disengagement)$ = probability of the AV disengagement is due to a certain category of cause, (i could be "Perception issue", "Planning issue" or "Control issue");

z_i = a linear function of multiple factors;

a_i = constant of the linear function of having an AV disengagement due to certain category;

x_{ik} = k^{th} variable significantly affects having an AV disengagement due to certain category;

β_k = coefficient of the k^{th} variable.

3.3.2. Binary logistic regression

The time spent on taking over the driving when requested is classified into two categories, which is either "within 0.5 s" or "above 0.5 s". Given this situation, the binary logistic regression model is suitable for modeling human drivers' take-over time needed when facing the AV disengagement as a function of multiple related factors from

Table 3
Proportions of Each Cause of Disengagement.

Cause of Disengagement	Aspects	Counts (Proportions)
Perception Issues 164 (33%)	Computation issues of perception	140 (28%)
	GPS, Localization issues	18 (4%)
	Hardware Sensors	6 (1%)
Planning Issues 301 (60%)	Undesired behaviors from road users	240 (48%)
	Computation issues of planning	50 (10%)
	Complete a lane change	11 (2%)
Control Issues 38 (7%)	Computation issues of controlling	18 (4%)
	Steering wheel issues	12 (2%)
	Acceleration/ Deceleration issues	8 (1%)

Table 2, as expressed by the following equations.

$$P(TOT = i) = \frac{1}{(1 + e^{-z_i})} \tag{4}$$

$$z_i = a_i + \sum_k \beta_k x_{ik} \tag{5}$$

where,

$P(TOT = i)$ = probability of the driver assumes manual control of the vehicle with a Take-Over Time of i (i could be "within 0.5 s" or "above 0.5 s");

z_i = a linear function of multiple factors;

a_i = constant of the linear function of the driver finishes the take-over process with a Take-Over Time of i;

x_{ik} = k^{th} variable significantly affects the driver finishes the take-over process with a Take-Over Time of i;

β_k = coefficient of the k^{th} variable.

3.3.3. Classification and regression tree model (CART)

Using a decision tree to classify a nominal dependent variable is called a classification tree (Ghasemzadeh et al., 2018). The classification can be defined as a procedure for understanding the mechanism for predicting a value in the dependent variable (Han and Kamber, 2011). If the dependent variable is categorical, CART produces a classification tree. If the dependent variable is numerical, CART produces a regression tree. In this study, both causes of disengagement and time needed for taking over can be considered as categorical variables.

In this study, the CART models are suitable for exploring the following dependent variables:

- Exploring the relationships between the causes of disengagements (an automated vehicle's disengagement caused by perception, planning, or control issues) and potential contributing factors.
- Exploring the relationships between Take-Over Time (TOT) and potential contributing factors.

The two basic components of classification tree models are the "root node" and the "leaf node" (Weng and Meng, 2011). The root node is divided into two child nodes with independent variable creating the best homogeneity. The dividing procedure would be repeated until all the data in each node reach their highest homogeneity. After several iterations, the terminal nodes are generated, which is considered to be the "pure" nodes.

The split criterion in the CART method selects Gini index as the purity indicator, which is applied to measure the contribution of each split towards maximizing the homogeneity through the resulting split (Huang et al., 2018). Gini is calculated in the following form:

$$gini = 1 - \sum_i^n p_i^2 \tag{6}$$

Where:

i = the category of the dependent variable;

n = the total number of the dependent variable;

p = the percentage of each category in the dependent variable.

Following this sequence, the classification tree can be plotted. The beauty of the CART model, compares with other machine learning techniques such as Random Forest, is that "leaf node" that impacts the nominal dependent variables can be quantitatively analyzed.

Normally, the classification models are built from a training dataset in which trends of explanatory and response variables are identified and used to predict the value of the dependent variable for the testing dataset (Kashani and Mohaymany, 2011). In this study, these classification trees can assist auto manufacturers to understand the mechanisms of automated vehicle disengagement.

4. Findings and discussions

4.1. Analysis of cause of disengagement

4.1.1. The cause of disengagement overview

Previous research already included an overview of the automated vehicle disengagements, including the trends of monthly miles and the disengagement frequency (Nissan, 2017; Delphi Automotive System, 2017). In this paper, to avoid repetition and provide a better view of the data, comparing each cause of disengagement using the automated driving system as a reference could be an alternative, as shown in Table 3.

As is shown in Table 3, disengagements caused by either perception or planning issues consist of 93% of the total records of automated vehicle disengagement.

For disengagements due to the perception issue, topping the list is "Computation issues of perception" (28%), followed by "GPS, Localization issues" (4%). Issues from hardware sensors consist of only 1% of the total disengagements. This indicates that hardware sensors can function well during the tests on public roads in California.

For all automated vehicle disengagements due to planning issues, it is found that "Undesired behaviors from road users" (48%) ranks the highest compares with "Computation issues of planning" (10%) and "Complete a lane change" (2%). This is due to the fact that automated vehicle tests were mostly taken place on street roads (see Table 2), where there are a larger number of road users compares with the freeway. In addition, the behaviors of these road users (i.e., pedestrians and cyclists) can be unpredictable. Therefore, under these circumstances, automated vehicles request human drivers to take over.

Disengagements due to the control issue consist of only 7% of the total disengagements. This means that there are rare chances that the current automated driving systems stop working due to a control issue.

In order to see the trends of each cause of disengagement from August 2016 to November 2017, two heatmaps are plotted in terms of different levels of driving automation, as illustrated in Fig. 2.

As shown in Fig. 2, it can be concluded that either Level 3 or Level 4 automated driving system have been facing the challenge from perception or planning issues throughout every month from August 2016 to November 2017. This finding is consistent with the results from Table 1.

The result also indicates another difference between Level 3 and Level 4 automated driving systems. Perception issues, along with planning issues, have also been challenging for the Level 3 automated vehicle disengagement in most of the public testing months as shown in (a). However, the disengagement due to perception issues is no longer the dominating factor contributing to the disengagement of the Level 4 automated driving system as shown in (b). It shows that Level 4 automated driving system has improved the performance in the perception phase.

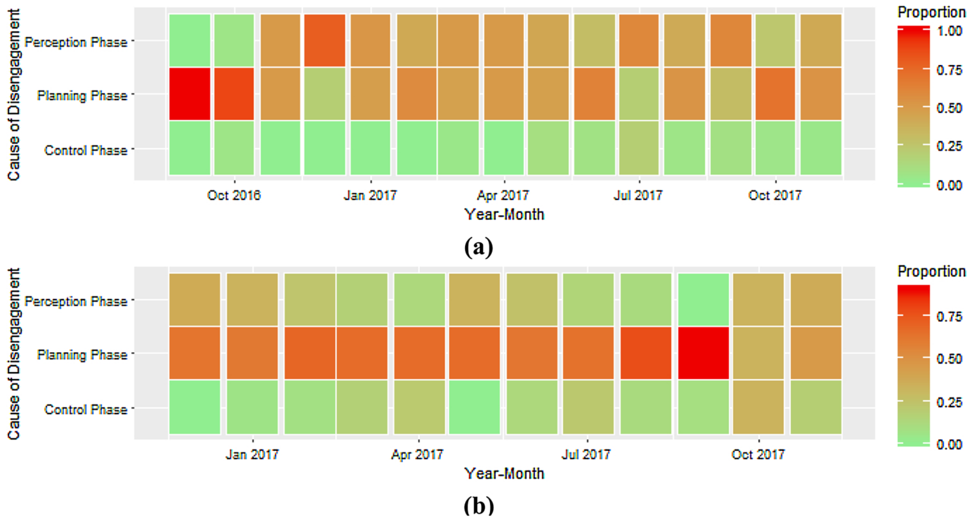

Fig. 2. The proportion of Each Disengagement Reason Per Month with Different Automated Driving Levels: (a) Level 3 AV; (b) Level 4 AV.

4.1.2. Exploring variables that result in causes of disengagements

In this section, the automated vehicles' disengagement occurred during the software computational platform is analyzed. To facilitate exploring the difference in the cause of disengagements among numbers of LiDAR, radar, camera sensors and roadway characteristics, a classification tree is plotted as illustrated in Fig. 3.

As illustrated in Fig. 3, variables including the number of hardware sensors (i.e., LiDAR, radar as well as camera sensors) and roadway characteristics are affecting the cause of disengagement. The percentages of observations in classification are also included in Fig. 3. Findings are summarized as follow:

- When automated vehicles are driving on the freeway, the vehicles are most likely to have perception issues than others. This is because the driving environment on the freeway is relatively simple than on the local roads. There are fewer traffic signals and fewer road users on the freeway compared with local roads, which automated vehicles do not make decisions frequently regarding stop/go and predict pedestrians/cyclists' behaviors. In addition, the numbers of hardware sensors installed on automated vehicles do not make a difference in the cause of disengagement while they are driving on the freeway.
- When automated vehicles are driving on the local roads, perception, planning, or control issues can occur with different combinations of LiDAR and radar sensors.
  - If the automated vehicles are driving on the local roads with 5 or fewer LiDAR and radar sensors installed, the automated vehicles are most likely to have the perception issue. Therefore, according to the classification tree, the perception issue can be addressed by either increasing the number of radar sensors or LiDAR sensors.

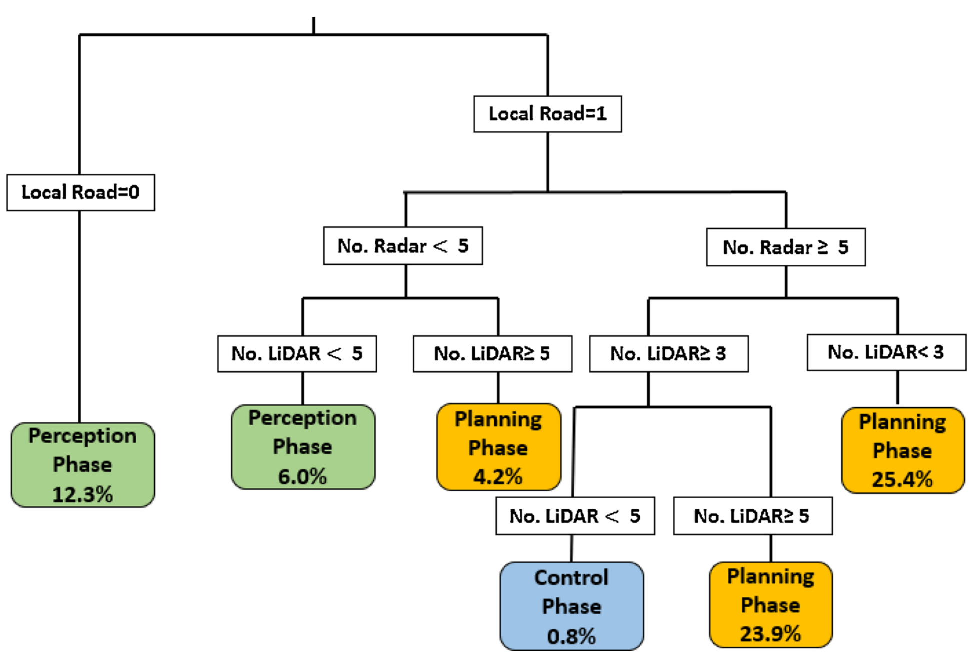

Fig. 3. Mechanism of the Cause of Disengagement.

- ○ The automated vehicles are likely to have the planning issues with the number of LiDAR sensors more than (or equal to) 5 or fewer than 3. This is because if there is a large number of LiDAR sensors installed on the vehicle, redundant data can be invited which could affect the computation of planning. In addition, if the vehicle operates with a small number of LiDAR sensor installed, the data can be insufficient which can also affect the computation of planning. Therefore, to address the planning issue, the optimum number of LiDAR sensors installed on automated vehicles is 3 or 4. As mentioned in the previous section that hardware sensors (i.e., LiDAR sensors) detect various types of objects on the road and then transfer the collected results to the software system of the automated vehicle for the process of perception, planning, and control. Possible reasons for having a limited number of LiDAR sensors installed can be explained by the limitation of the computational power of the software system. Despite adding more LiDAR sensors on the automated vehicle can provide more sufficient information about the driving environment, this can also lead to computational errors for the current automated driving software system due to excessive computational burden. Several studies have shown that the computational burdens exist while the AV is making decisions of driving or controlling itself (Li et al., 2017; Pendleton et al., 2017; Guo et al., 2018; Hussain and Zeadally, 2018). Thus, there is still a trade-off between the number of LiDAR sensors and the computational power of the current software system. From the perspective of preventing crashes, it is expected that AVs might be more beneficial to have more than four LiDAR sensors in the future while the computational power becomes stronger.
- ○ For the control issues, the classification tree reveals similar results with the results in Table 3, which control issues rarely occur. This is because the perception and planning issues of automated vehicles usually come from the artificial intelligence problem, which is a major challenge for all automated vehicle manufacturers. The control issues of the automated vehicles are often associated with the mechanical performance of the vehicle. Issues such as accelerating or decelerating heavily can be addressed from the perspective of mechanical techniques.

- To summarise, the classification tree delivers an idea that the disengagement issues of automated vehicles can be addressed by shifting the issues from perception to control aspects. Therefore, for automated vehicles traveling on either freeway or local roads, it is recommended to installing 5 or more radar sensors as well as 3 or 4 LiDAR sensors. For the number of camera sensors, automated vehicle manufacturers can stay with their current plans on the number of camera sensors installed without any suggested changes.

4.1.3. Ordinal logistic regression of automated vehicle cause of disengagement

Following the procedure of how automated vehicles operating on the road, the causes of disengagement have a meaningful order that automated vehicle disengagement occurs from perception to control phase. Therefore, the ordinal logistic regression model is suitable for analyzing the contributing factors to the cause of disengagement. Table 4 summarizes the ordinal logistic regression for the cause of disengagement. In Table 4, B is the coefficient of the independent variable; S.E. stands for the standard error associated with the coefficient; Wald is the Wald chi-square value; df represents for the degree of freedom; Sig. is the p-value; and Exp(B) represents for the odds ratio.

Table 4
Ordinal Logistic Regression for Cause of Disengagement.

	B	S.E.	Wald	df	Sig.	Exp (B)
Dependent Variables						
COD = Perception Issue	−1.344	0.237	32.175	1	0.000*	0.261
COD = Planning Issue	2.262	0.258	77.179	1	0.000*	9.602
Independent Variables						
Number of LiDAR Sensors (1)	0.617	0.223	7.631	1	0.006*	1.853
Number of Radar Sensors (1)	−0.897	0.212	17.951	1	0.000*	0.408
Number of Camera Sensors (1)	−0.156	0.203	0.588	1	0.443	0.856
Roadway Characteristic (0)	−2.039	0.340	35.914	1	0.000*	0.130

Note that (1) independent variables in the ordinal logistic model are categorical, see definitions in Table 2; (2) "*" indicates significant variables (p-value less than the cut-off value of 0.05).

The modeling results from Table 4 show similar results with the classification tree. Significant variables of numbers of LiDAR sensors, numbers of radar sensors, and roadway characteristic affect the cause of disengagement. The independent variable of “Roadway Characteristic (0)” has a negative estimated coefficient of −2.039, indicating that freeway is a significant roadway to invite perception issues of the automated vehicles at the confidence level of 95%. The odds ratio for “Roadway Characteristic (0)” is 0.13, which means that the automated vehicles traveling on the freeway are 0.13 times more likely to encounter a perception issue. The independent variable of “Number of Radar Sensors (1)” has a negative estimated coefficient of −0.897, suggesting that fewer numbers of radar sensors significantly affect automated vehicles to have a perception issue at the confidence level of 95%. The odds ratio for “Number of Radar Sensors (1)” is 0.408, which means that automated vehicles installed with a smaller number of radar sensors (9 or fewer) are 0.408 times more likely to have a perception issue. The numbers of camera sensors don’t make a difference in affecting the cause of disengagement. All these findings are consistent with the results in analyzing the classification tree of the cause of disengagement (Fig. 3).

4.1.4. Discussion

Tables 5 and 6 summarize the breakdown of model accuracy for each category using the classification tree and ordinal logistic regression model. Basically, both models have an overall accuracy rate above 70%. The classification tree model is able to classify all causes of disengagements, with 95.3% classification accuracy in disengagement in the planning phase. The ordinal logistic regression has an overall accuracy of 71.4%. Although it has a higher accuracy rate in predicting disengagement due to a planning issue than a classification tree, it fails to predict disengagement due to a control issue.

To summarize, both the classification tree and ordinal logistic model of causes of disengagements indicate how a number of hardware sensors as well as locations, could affect the cause of disengagement. Considering the fact that the classification tree model well-classified all causes of disengagements, it is recommended for further use in exploring the mechanism of automated vehicle cause of disengagement.

4.2. Analysis of time needed for taking over: Take-Over Time (TOT)

4.2.1. Exploring the mechanism of TOT

In this section, the mechanism of TOT is explored using the classification tree. Based on the automated vehicle disengagement reports, no report reveals that whether test drivers were informed about the information regarding what is level of automation and how many hardware sensors installed on the automated vehicle. Therefore, in this study, these two variables are not included in the classification tree. Fig. 4 illustrates the classification tree regarding TOT.

As illustrated in Fig. 4, roadway characteristics and cause of disengagement affect the time needed to take over for test drivers. The percentages of observations in classification are also included in Fig. 4. Findings are summarized as follow:

- When automated vehicles are traveling on the local roads, test drivers are most likely to take over the driving within 0.5 s if the automated vehicle requests the driver to do so or the driver take over by himself due to consideration of safety operations. This is because

Table 5
Model Accuracy for Cause of Disengagement Classification Tree.

Overall Accuracy:	76.1%	(383/503)	Predicted Values		
			Perception Phase	Planning Phase	Control Phase
Ground Truth Values		Perception Phase	56.1% (92/164)	41.5% (68/164)	2.4% (4/164)
		Planning Phase	4.3% (13/301)	95.3% (287/301)	0.4% (1/301)
		Control Phase	36.8% (14/38)	52.6% (20/38)	10.6% (4/38)

the automated vehicle disengagement database indicates that 85% of the disengagements occurred on local roads. In addition, according to the automated vehicle database, 80.7% of the disengagements occurs when drivers take over within 0.5 s on local roads. It also reveals that drivers' take over time while driving on local roads is not affected by the cause of disengagements.

- When automated vehicles are traveling on the freeway, the cause of disengagement determines how long it takes drivers to take over. As shown in Fig. 4, disengagements caused by either the perception or the control issue extend the take over time. It is important for drivers to take over as soon as possible if needed. For the extended take-over time due to a control issue, it can be addressed by focusing on the interaction between the automated driving system and the vehicle itself.

To summarize, drivers can take over within 0.5 s on the local roads for most of the time. Automated vehicles disengagement due to a perception or a control issue on the freeway extends the time needed to take over. Further studies can focus on addressing these two issues on the freeway.

4.2.2. Identifying significant factors contributing to take-over time

To identify significant factors contributing to take-over time, the binary logistic regression model is applied. Table 7 provides the statistical results of the analysis of take-over time. In Table 7, B is the coefficient of the independent variable; S.E. stands for the standard error associated with the coefficient; Sig. is the p-value; and Exp(B) represents for the odds ratio.

Findings are summarized as follows:

The result shows that p-values for "Local roads" and "COD = Planning Issue" are smaller than 0.5. It means they are significant factors that impact take-over time at the confidence level of 95%. "Local roads" has a negative coefficient of -3.335 and an odds ratio of 0.036, which means that take-over time is significantly shorter (0.036 times) on the local road than on the freeway. "COD = Planning Issue" also has a negative coefficient of -2.515 and an odds ratio of 0.081, suggesting that disengagement due to a planning issue would need shorter time for taking over the driving, compares with disengagements caused by either the perception or the control issue. All the findings from the binary logistic regression results are consistent with the ones in the classification tree.

4.2.3. Discussion

Tables 8 and 9 summarize the accuracy in classifying and predicting take-over time. Both the classification tree model and binary logistic model show the 93% overall accuracy. Given the fact that the classification tree shows the hierarchical structure of variables that impact take-over time, it is recommended to use the classification tree model in predicting the take-over time.

5. Conclusions

Using multiple modeling approaches involving statistical modeling and classification tree, identification of the contributing factors that impacted the automated vehicle cause of disengagement and human drivers' taking over are conducted. Ultimately the mechanisms of the automated vehicle disengagements and take-over time are explored as well. All findings show consistent results between the classification tree model and a statistical model.

In conclusion, to improve the automated driving systems with fewer disengagements, it is recommended to install 5 or more radar sensors on automated vehicles. An optimum number of LiDAR sensors to be installed is 3 or 4. The number of cameras can be customized based on the preference of each automated vehicle manufacturer. To address the extended take-over time issue, driving an automated vehicle on local roads or driving an automated vehicle on the freeway while encountering planning issues can keep the take-over time within 0.5 s. Further studies should be focused on how to address the extended take-over time issue when automated vehicles are traveling on the freeway with perception or control issues.

Since this study only focuses on exploring causes and effects of disengagements initiated by AV, therefore, human drivers' behaviors in response to either Level 3 or Level 4 driving automation remain unknown. In future research, it is expected that the behavioral adaptation of human drivers towards AV technology can be further investigated in the field or simulation driving environment.

One limitation of this study is regarding the data collection process. As mentioned, there is no standard format for each automated vehicle manufacturer to submit their disengagement annual report. it takes some time to search for the missing values (i.e., hardware sensors installed when testing in public) in the dataset. In addition, the drivers in these automated vehicles are test drivers, which cannot represent consumer drivers. There might be a difference between test drivers and consumer drivers in dealing with automated vehicle disengagements. For example, the test drivers' take over time is probably the very best case as their responsibility is to monitor the automated driving system closely. Therefore, the results can be helpful for automated vehicle manufacturers but cannot be directly generalized for consumer drivers.

Last but not least, the author recommends AV companies to include meteorology and illumination data in the disengagement reports as the

Table 6
Model Accuracy for Ordinal Logistic Regression Model.

Overall Accuracy:	71.4%	(359/503)	Predicted Values		
			Perception Phase	Planning Phase	Control Phase
Ground Truth Values		Perception Phase	42.1% (69/164)	57.9% (95/164)	0% (0/164)
		Planning Phase	3.7% (11/301)	96.3% (290/301)	0% (0/301)
		Control Phase	26.3% (10/38)	73.7% (28/38)	0% (0/38)

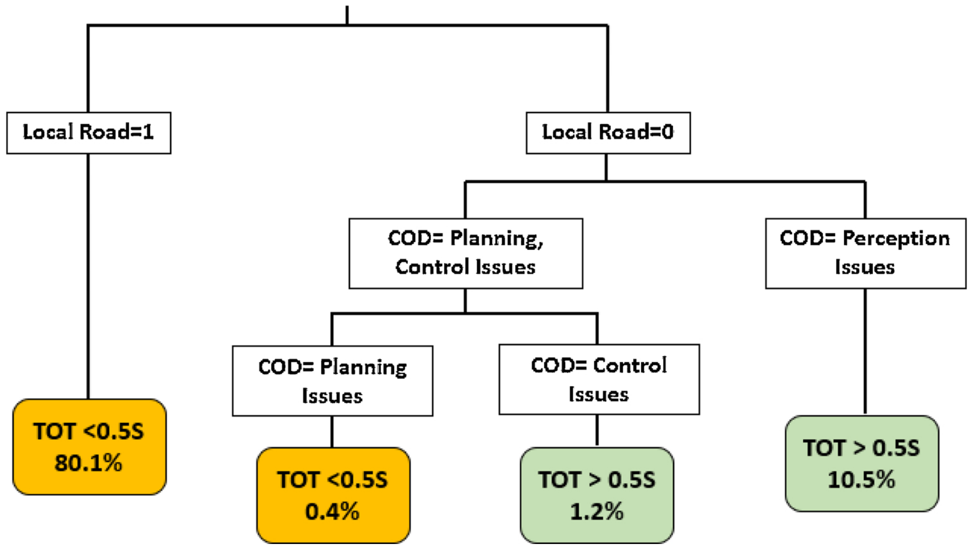

Fig. 4. Mechanism of Take-Over Time.

Table 7
Binary Logistic Regression Results for Take-Over Time.

	B	S.E.	Sig.	Exp (B)
Constant	1.052	0.529	0.047*	
Local roads	−3.335	0.389	< 2e-16*	0.036
COD = Perception Issue	0.600	0.530	0.257	1.822
COD = Planning Issue	−2.515	0.771	0.001*	0.081

* Indicates significant variables (p-value less than the cut-off value of 0.05).

Table 8
Model Accuracy for the Classification Tree Model.

Overall Accuracy: 93.0%	(468/503)	Predicted Values	
		TOT < 0.5 s	TOT > 0.5 s
Ground Truth Values	TOT < 0.5 s	96.9% (409/422)	3.1% (13/422)
	TOT > 0.5 s	27.2% (22/81)	72.8% (59/81)

Table 9
Model Accuracy for the Binary Logistic Regression Model.

Overall Accuracy: 93.0%	(468/503)	Predicted Values	
		TOT < 0.5 s	TOT > 0.5 s
Ground Truth Values	TOT < 0.5 s	96.9% (409/422)	3.1% (13/422)
	TOT > 0.5 s	27.2% (22/81)	72.8% (59/81)

former variable might affect functions of hardware sensors and the latter variable might affect the perception-reaction time of human drivers towards disengagements.

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