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Development of Machine-Learning Models for Autonomous Vehicle Decisions on Weaving Sections of Freeway Ramps

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Development of Machine-Learning Models for Autonomous Vehicle Decisions on Weaving Sections of Freeway Ramps

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16. Abstract

This research aims to develop human data-driven automated lane-change models for freeway weaving sections using computational methods that assist drivers taking an exit ramp or entering a freeway. A naturalistic driving dataset with 108 adult drivers served as the data source to observed drivers' lane change maneuvers over 53 freeway weaving sections in southeastern Michigan area. With the Cox proportional hazards model, we could identify at least 83% of weaving initiation time and provided at least 81% of accuracy for the models. The models were further evaluated based on computer simulations, which showed that collisions with the other vehicle in the target lane might occur if the ego vehicle drove with a same speed as that vehicle. Also, the ego vehicle would possibly decide not to engage a lane change before reaching the end of the weaving section if the driving speed was greater than 70 mph and the other vehicle with 55 mph or higher. As successfully implementing the models to an autonomous driving platform at Mcity, no physical traffic could be applied since the models did not provide a complete collision-free environment. Therefore, an augmented reality environment was adopted, for which the autonomous vehicle interacted with a 'ghost' car simulated by ROS signals and no 'virtual' collision was observed in the demonstrations. Further improvement for the models is needed, including the variety of the weaving scenarios from the data for model development and the consideration of speed adjustment for the autonomous vehicle before entering the weaving sections.

17. Key Words	18. Distribution Statement
Weaving sections, lane change, decision-making, survival analysis, safety	No restrictions.

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1. INTRODUCTION

In the US, freeway weaving sections are a very common design for ramps, which are most often found between the loop ramps of a cloverleaf interchange. A weaving section is usually composed of an onramp (entrance) followed by an offramp (exit) connected by an auxiliary lane for speed adjustment. Therefore, vehicles on the onramp and offramp need to weave in the auxiliary lane of limited length. Four types of traffic movements occur on a freeway weaving section include: freeway-to-freeway (a non-weaving movement), freeway-to-offramp (a weaving movement), onramp-to-freeway (a weaving movement), and onramp-to-offramp traffic (a non-weaving movement). For vehicle automation of level 3 or higher, the automated driving system (ADS) should handle all dynamic driving tasks, with human drivers as the supervisor to intervene if needed. Before engaging a weaving movement, ADS needs to decide when and how the weaving behavior should be safely executed, based on vehicle kinematics, ramp geometry, the behavior of the other weaving/non-weaving vehicles surrounded, and other important factors. Safety for weaving movement is important because merging onto the freeway via entrance ramp and getting off the freeway via exit ramp account for more crashes than any other segments of the highway (McCartt et al., 2004).

There is limited research specifically for weaving sections. Many previous studies have been focused on highway on-ramps (summarized by Zhu et al. (2022)) and off-ramps (Dong et al., 2020) from the perspectives of safety and traffic flow efficiency, especially impact on the mainline traffic flow. However, for regular ramps, the traffic in the adjacent lane does not actively weave into the ego lane. Furthermore, the existing research on the weaving behavior was algorithm-driven based on a series of assumptions and constraints (Amini et al., 2021; Nagalur Subraveti et al., 2021; Jin, 2013). Among those studies, optimization was the most common method to develop the models, which were not necessary driver centered. Therefore, in this study, we applied a data-driven method that investigated drivers' weaving behavior in a safe manner to induce models. To achieve the goal, we first identify the causes of the crashes in highway ramps and weaving sections. With such information, we explored weaving behavior data from a naturalistic driving dataset by extracting critical factors and countermeasures over a weaving maneuver. Weaving decision-making models would be developed via the data exploration and be validated in a computer simulation environment. Finally, the decision-making models would be implemented to an ADS platform to showcase automated weaving maneuvers that interacted with the traffic in the adjacent lane.

1.1 Highway Weaving Safety

Previous studies have concluded the factors of safety impact on freeway ramps, including the number of lanes, exit type (on/off), ramp side (left/right), ramp capacity, ramp speed limit, combined length of ramp and auxiliary lanes, and traffic speed (Bared et al., 2005; Bauer &

Harwood, 1998; Chen et al., 2009; Chen et al., 2011; McCartt et al., 2004). As a special design of ramps, for weaving sections the effect of these factors can differ and many of them should be considered simultaneously, such as the traffic speeds for both the ego and target lanes and the length of the weaving section. The challenge for human drivers is that all the factors need to be synthetically considered within few seconds during the weaving maneuver, given the limited length of the weaving section. It was found that shorter gap while changing lanes would increase the lane change decision duration (Sun & Feng, 2023) and the driver might more possibly miss the exit or entrance. So far, algorithms developed for weaving section are macroscopic that estimate the traffic density, average/approximate traffic speed, or accident, to build traffic models for weaving section design. The 2010 Highway Capacity Manual also provided very thorough review about the prediction for the rate of lane changes in weaving sections, average speed of weaving vehicles, and weaving section capacity (HCM 2010, 2010). However, it was unknown if the prediction or suggestion for changing lanes met the driver's expectation.

1.2 Objectives

This research intends to address this issue by investigating human drivers' lane change decisions in freeway weaving sections with the presence of vehicles in the adjacent lane. The weaving scenarios include "entering the freeway" and "taking the exit ramp". In the first phase, drivers strategically adjust the speed to match the traffic speed in the target lane. The longitudinal speed control is very important in this phase because the speed limit in the weaving section can be much lower than on the freeway through lanes. The traffic in the auxiliary lane will affect drivers' speed control. Then the driver begins to merge into the auxiliary lane for the exit or into lane 1 for entrance, in which drivers' behavior will be greatly affected by the ramp geometry and the other vehicles' positions and relative speeds. For example, the on-ramp vehicles may first enter the weaving section and occupy the later part of the auxiliary lane, so the weaving driver should pay attention to that on-ramp vehicle and how far the off-ramp is. This is just a very typical situation, and the real world will not cooperate. Finally, the weaving maneuver is complete, and the vehicle stays in the target lane. Therefore, this study will comprehensively observe the factors with impact on the weaving decision.

Three main tasks in this research include, (1) identifying surrounding vehicles' positions and relative speeds, (2) developing models to predict how the weaving decision is made, and (3) implementing the developed models in Mcity's automated vehicle to engage lane changes in the weaving sections at Mcity Test Facility. Introducing these findings can help companies develop automated systems that refer to driver-acceptable and safe strategies to interchange with vehicles in the weaving section of limited length.

2. METHOD

2.1 Weaving Section Selection

The research team selected 53 weaving sections on US highways in the southeastern Michigan, where most of the naturalistic mileages were collected. Figure 1 shows a typical weaving section on Interstate-96, and its starting and ending points. The locations of all selected weaving sections in the southeastern Michigan are shown in Figure 2.

Figure 1. A weaving section on I-96

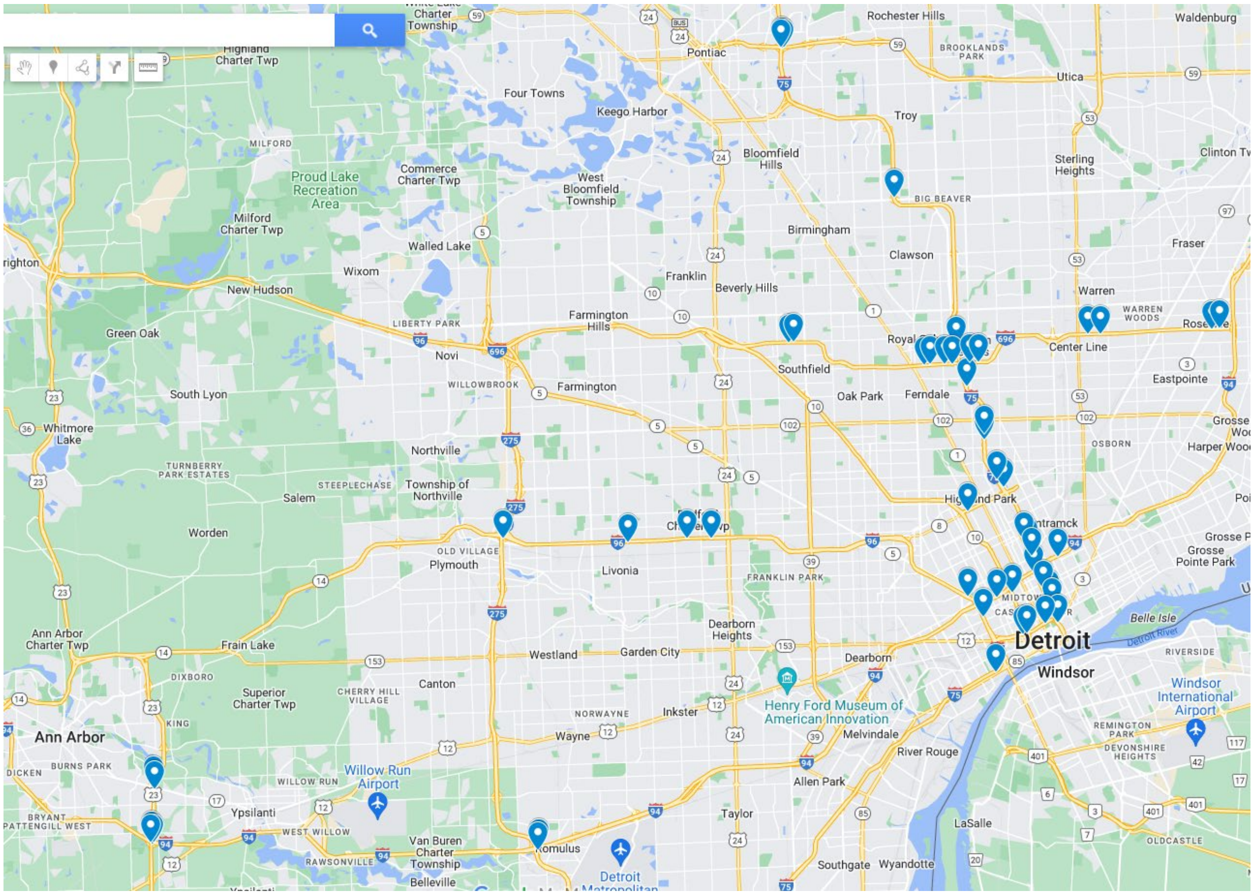

Figure 2. Locations of selected weaving sections

The length of each weaving section was estimated using the latitude and longitude of the weaving section’s starting and ending points, which were defined as the merge and fork of the outer and auxiliary lanes, respectively. The distribution of the length is shown in Figure 3, with the minimum, average, and maximum lengths of 127 m, 402 m, and 1101 m.

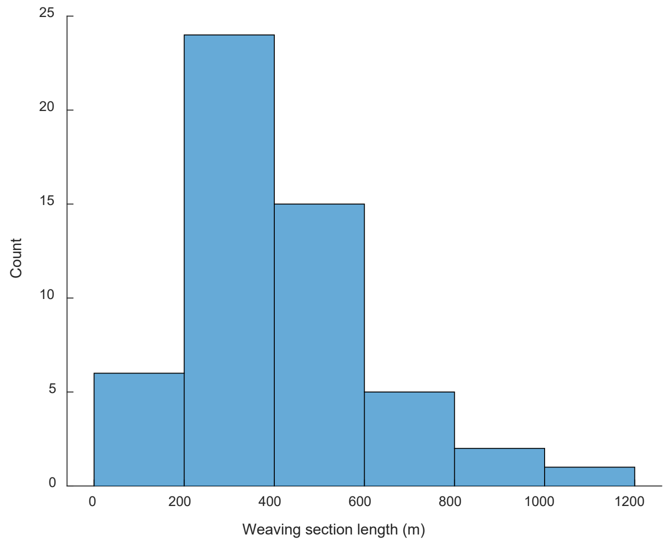

Figure 3. Distribution of the length of selected weaving sections

Besides the lane changes in weaving sections, we extracted the lane changes towards/from the regular freeway ramps, which indicated a simple exit or entrance without weaving. Given the great number of the regular ramps and the challenges to define a starting point of a regular ramp, no data for the length of the ramps were identified. The models of lane changes at regular ramps would be compared to the weaving models.

2.2 Naturalistic Driving Field-Operational-Test Data

The naturalistic driving data used in this study were derived from the Integrated Vehicle-Based Safety System Field Operational Test (IVBSS FOT) database, which included the driving data and videos of 108 adult drivers (balanced for age: 20-30, 40-50, and 60-70 years old, and sex), and more than 200,000 driven miles (Sayer et al., 2010). Over 200 signal channels and 5 video channels (forward scene, back scene from left mirror, back scene from right mirror, face, and cockpit) were collected in the IVBSS FOT and synchronized to the sampling rate of 10 Hz. Given the scope of this study for the lane change behavior in weaving sections, the time window for data collection started from when the vehicle just entered the the weaving section until 5 seconds after the weaving behavior. More than twenty variables were extracted, which included (1) vehicle dynamics: longitudinal and lateral speed and acceleration, steering angle, yaw rate, turn signal engagement, conventional cruise control engagement; (2) roadway design: number of lanes, lane boundary type, road curvature, road type; and (3) surrounding vehicle (private-owned vehicle: POV) information: range, range rate. These variables were used for data filtering, computational modeling, or validation. The videos provided additional qualitative information that was used to identify qualified weaving sections and regular ramps. The length of a weaving section was determined by the longitude and latitude of the two gore points for the beginning and end of the weaving section. All the variables are listed in Table 1, including 18 directly extracted from the IVBSS database and 6 by further computation.

Table 1. Variables Extracted from IVBSS Naturalistic Driving Data

Variable	Unit	Description
(a) Variables extracted from the database		
Driver ID	integer	Driver index number
Trip ID	integer	Trip index number for each driver
Time	s	Timestamps, accurate to 0.1 s
Weaving time	s	Time when the weaving maneuver occurred
Accelerator pedal	%	Accelerator pedal position
Brake pedal	binary	Brake pedal application
Travel distance	m	Travel distance for each trip
Cruise control engagement	binary	Use of conventional cruise control
Longitudinal speed	m/s	Travel speed
Lateral speed	m/s	Lateral movement speed referring to the lane boundary
Steering angle	degree	Steering wheel rotation angle
Turn signal engagement	binary	Use of turn signal
Wiper	binary	Use of wipers
Heading angle	degree	Heading with respect to the GPS
Latitude and longitude	float	Location of the vehicle provided by GPS
Lane boundary type	integer	Lane boundary type index
Lane offset	m	Lateral distance from the center of the ego lane
Lane offset confidence	%	Confidence of lane offset estimation
(b) Computed variable		
Distance to weaving section starting point	m	Distance between the ego vehicle and the starting point of a weaving section
Distance to weaving section ending point	m	Distance between the ego vehicle and the ending point of a weaving section
Weaving point	ratio	The ratio between the distance to the starting point and the length of the weaving section; the proportion of the weaving section the AV had passed
Longitudinal distance to POV	m	Longitudinal distance between POV and the center of AV
Lateral distance to POV	m	Lateral distance between POV and the center of AV
Range rate	m/s	Change of the distance between POV and AV per second (relative speed)

To simplify the effect of POV and enhance the accuracy of the POV position, we only considered the nearest POV from the ego vehicle either in the target lane (adjacent lane ego vehicle was moving towards) or in the ego lane. The vehicles in the other side were ignored since they should not affect the weaving behavior.

2.3 Computational Modeling Methods

In the original statement of work, machine-learning methods and logistic regressions were the proposed methods to train and build the decision-making classifications. However, there was no lane change counterfactuals defined from the dataset as a 'no-go'. All events for modeling were successful lane changes in weaving sections (no aborted lane change event was included), and there were no misses because we could not separate the misses from the passes through the weaving sections without feedback from the drivers. Furthermore, the research team found that the association between lane change decision and the potential predictors was not trainable in a typical way, due to the following characteristics of weaving events.

- Enforcement: The driver must change lanes; otherwise, they missed the exit or entrance.
- Self-correlation: A driver might have multiple weaving events and these events were correlated within each driver.
- Time-varied variables: The time elapsed played an important role to the lane change decision. The critical factors and covariates were time-varied.
- Censored observation: Observations before the start of weaving were treated as censored, which meant a weaving event had not occurred yet.

Therefore, survival analysis was selected as the method that associated the time-varied covariates with a simple outcome. Survival analysis is a useful statistical method that has been used in different applications, such as medical informatics (patient survival outcomes), engineering (product reliability, machine lifetime), employment (employee churn rates), and economics (change in the valuation of liability). The general idea is to estimate the lifetime (period from birth event to death event) in different conditions. Some observations were 'censored,' which meant an event was not observed over a period of time. Applied to this study, each weaving event included the time the driver stayed in the ego lane under certain conditions (lived) for 4 seconds and the time they started weaving (died) for 1 second. The 5-second time window ensured that all data were collected after the vehicle passed the gore point of a weaving section. Then a single weaving event was further broken down to 5 segments, and each lasted for 1 second (4 non-weaving, 1 weaving). These segments served as potential samples for modeling.

The Cox proportional hazards model (Cox, 1972) was selected to conduct the survival analysis, shown as Eq (1):

$$\frac{h(t\ )}{h_0(t)} = \beta\ _0 + \quad _1 \quad _1 + \beta\ _2 X\ _2 + \cdots + \beta\ _n X\ _n + \epsilon \qquad (1)$$

where $\frac{h(t\ )}{h_0(t)}$ is the survival ratio at instant time t, $\beta\ _0$ the constant, and $\beta\ _i$ the coefficient for each covariable in the model. Therefore, the exponential presentation of these coefficients is the hazard ratio (HR, $\frac{h(t)}{h_0(t)}$), which could be interpreted as the <u>ratio of lane change probabilities</u> for this study. In this study, all the covariates were numerical (continuous), and we wanted to determine how the probability of a lane change event varied as the variables increased by one unit (%, m, m/s, etc.). Same as the assumptions for linear or logistic regressions, there should not have collinearity among the covariates, so the predictors needed to be selected carefully.

After reviewing the variables listed in Table 1, the following covariates were firstly selected, along with their possible correlated variables that should NOT be used for the Cox proportional hazards model:

- Longitudinal speed: accelerator pedal position, longitudinal acceleration, brake pedal, cruise control engagement
- Lateral speed: steering angle, lateral acceleration, heading angle
- Weaving point: travel distance, distance to weaving section starting/ending points
- Longitudinal distance to POV
- Lateral distance to POV: lane position
- Range rate to POV

With the significant factors tested through the survival analysis, the models supporting weaving decision would be implemented by outputting weaving suggestions in real time.

2.4 Model Evaluation

With the results from the Cox regression, we would first review survival curves with the Kaplan-Meier method (Bland & Altman, 1998) that calculated the **non-weaving probability** at different time before weaving. To evaluate the performance of the weaving classification models, confusion matrices based on different classification thresholds would be first generated, followed by the receiver operating characteristic curve (ROC curve) with the aggregated information from the confusion matrices, and the area under the curve (AUC). A five-fold repeated cross validation was further conducted to train the model using different portions of the data. With this method, the cross validation would be repeated for 100 iterations, for which a lane change event at weaving sections or regular ramps in each run was randomly assigned to a fold as validating cases and the other four folds as training cases that trained surrogate models. After this procedure, we would have 500 (100x5) surrogate models trained that would be applied to corresponding validating cases to generate predictions. Then, we would select the true positive rate (TPR, sensitivity), true negative rate (TNR, specificity), false positive rate

(FPR), accuracy, and positive predictive value (PPV), based on the optimal threshold from the classification models.

2.5 Computer Simulation

The validated weaving-decision-making models would be first tested in a virtual environment using MATLAB Simulink before any deployment at Mcity, due to safety concerns. With the virtual Mcity map supported by Simulink, we were able to simulate the movements and trajectories of the AV that weaved with the presence of POV. The goal of the simulation was to understand the model performance and limitations, and to observe if there was any risky situation the research team did not think of. The AV and POV were assigned with the speeds from 25 to 75 mph with 5 mph as the segment (11*11 combinations in total) and departed from the positions from 70 meters before the gore point of the weaving section. Each speed combination was simulated for 100 times and the performance would be averaged. The metrics shown in Table 2 would be applied to verify the performance of the models.

Table 2. Model performance metrics with computer simulation

Metric	Description
Probability of missing an exit/entrance	The probability of missing an exit or entrance over the 100 repeated simulation trials
Probability of collision with POV while weaving	The probability of collision in the weaving section with POV over the 100 repeated simulation trials
Minimum gap	The shortest gap between AV and POV when AV was driving in the weaving section
Lane-change lateral speed	The lateral speed of changing lanes to successfully taking an exit/entrance

2.6 Mcity Automated Vehicle Setup and Demonstration

Mcity's Lincoln MKZ served as the automated vehicle platform with the computational models. However, during the period of the project, using multiple vehicles to implement the weaving scenarios was not approved even with an in-vehicle fallback test driver, unless the scenarios were collision free. Hence, the research team took a fallback position by using POV in terms of the augmented reality (AR) environment. In other words, AV would be only vehicle on the test track that interacted with a simulated virtual (ghost) POV. The goal of this task was to demonstrate the platform with the capability of customizing decision models in an AV that could interact with a POV.

Figure 4 shows the configurations between AV and POV. The AV was operated under the ROS framework and could be manipulated through the interfaces by subscribing the ROS topics of "/mkz_bywire_intf/control" to input the parameters of throttle (0-1), brake (0 or 1), and steering angle (rad) from a ROS node controlled by an external computer. The ROS node also handled the movement of POV and output the throttle, brake, and steering angle commands to AV based on the calculation by the survival models. In other words, AV always listened to the ROS node to engage any maneuver.

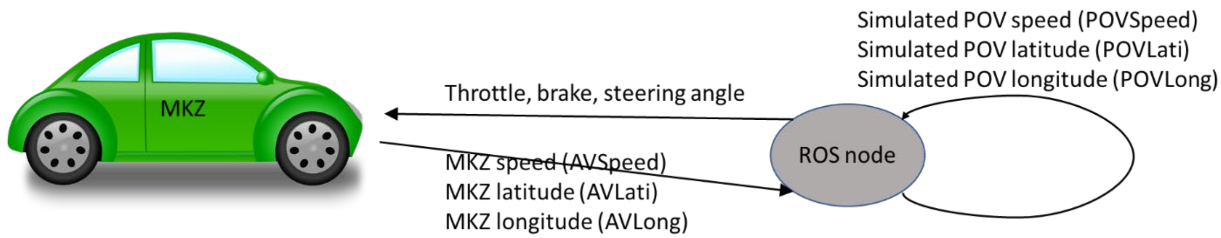

Figure 4. Framework of the communication between AV and POV

3. RESULTS

There were 101 weaving events for taking a freeway exit and 184 for a highway entrance, with 412 and 789 data points, respectively. Although a 5-second window was proposed for each weaving event, the samples without successful or reliable detection for POV were filtered, which excluded 18% of exit and 14% of entrance events. We also collected 1,869 events at typical exit ramps and 1,690 at entrance ramps as the reference, excluding the information of weaving position. Models for taking an exit and entrance were conducted, analyzed, and implemented separately.

3.1 Weaving Decision-Making Models – Towards an Exit Ramp on the Right

3.1.1 Cox regressions

Two Cox regressions were developed, of which the first tested all the six covariates listed in Section 2.3 and the second regression only included the significant covariates from the first regression. As shown in Table 3a, six variables were testes and four significant variables (bold fonts) were identified to model the lane change probability: speed, lateral speed, weaving position, and range rate. Longitudinal and lateral ranges were not significant as drivers had more concerns of the relative speed (range rate) and their speed. The coefficients show that the lane change probability increased as lower speed, greater lateral speed towards the right, later weaving position, and smaller range rate to POV. Same findings were concluded for the lane change decision at regular highway ramps (see Table 3b), which supported the results for weaving sections. With the coefficients, the estimate for the weaving decision could be calculated.

Table 3. Cox model for lane change probability: weaving section towards an exit

	(a) Weaving section				(b) Regular off-ramp			
	β	Z	p	β (Final)	β	Z	p	β (Final)
Speed	-0.041359	-2.48	0.01	**-0.04053**	-0.003648	-1.82	0.07	**-0.003508**
Lateral speed	-0.928869	-3.06	0.002	**-0.90654**	-0.207068	-6.77	<0.001	**-0.206317**
Weaving position	0.450558	2.19	0.03	**0.40151**	**N/A**	**N/A**	**N/A**	**N/A**
Longitudinal range	0.001009	0.55	0.58	-	0.000348	1.27	0.20	-
Lateral range	0.012313	0.41	0.68	-	-0.002855	-0.88	0.37	-
Range rate	-0.024710	-1.93	0.05	**-0.02568**	-0.010270	-3.18	0.001	**-0.010834**

The Kaplan-Meier survival curves shown in Figure 5 indicated that at one second before a true weaving event (between 4 and 5 s), more than 80% of the data were classified as not initiating a weaving. At 5 and 4 seconds before a true weaving maneuver (between 0 and 2 s), 100% of the event had no weaving predicted to begin.

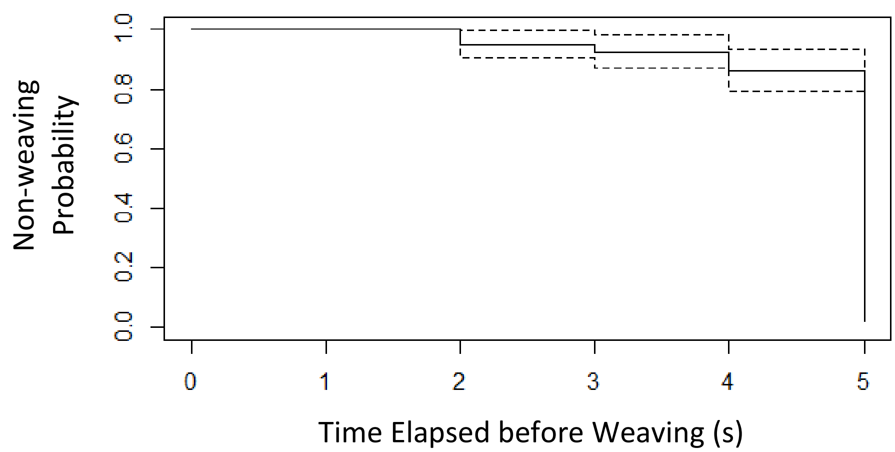

Figure 5. Kaplan-Meier survival curve with 95% confidence intervals for weaving towards an exit

3.1.2 Decision classification and performance

The ROC curve is shown in Figure 6, with AUC of 0.89, which was promising. The confusion matrix for the classification models is shown in Table 4 with the information of actual observations and predictions. It was found that the model could identify 87% of the presence of weaving (TPR) and 80% of the absence of weaving (TNR), with the accuracy of 81%. With FPR as 20% and FNR as 13%, the classification missed fewer weaving events, but also led to more false alarms. One should evaluate the cost trade-offs between missing an exit ramp and colliding with other vehicles if a lane change was triggered at inappropriate time. In this research, the cost of them was assumed to be the same.

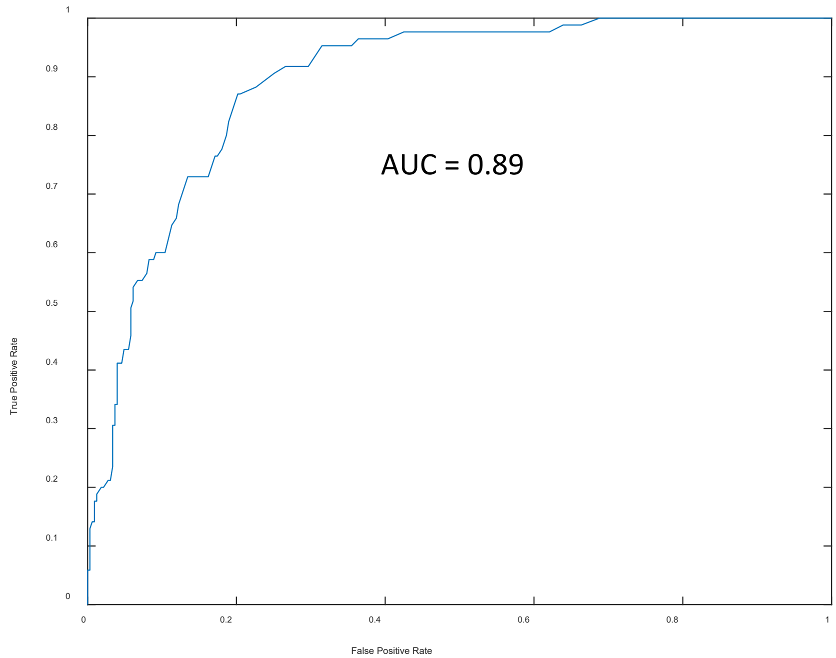

Figure 6. ROC curve for weaving decision classification when taking a highway exit

Table 4. Confusion matrix for weaving decision classification when taking a highway exit

Total observations = 412		**Predicted**	
		Lane change	No lane change
Actual	Lane change	74	11
	No lane change	66	261

3.2 Weaving Decision-Making Models – Towards an Entrance on the Left

3.2.1 Cox regressions

Table 5 shows the results from a Cox regression. As shown in Table 5a, three significant variables were identified to model the lane change probability: lateral speed, weaving position, and lateral range. The coefficients show that the lane change probability increased as lower speed, greater lateral speed towards the right, later weaving position, and smaller range rate to POV. Similar findings were concluded for the lane change decision at regular highway ramps (Table 5b), which supported the results for weaving sections. With the coefficients, the estimate for the weaving decision could be calculated.

Table 5. Cox model for lane change probability: weaving section towards an entrance

	(a) Weaving section	**(b) Regular off-ramp**

	β	Z	p	β (Final)	β	Z	p	β (Final)
Speed	-0.010504	-0.92	0.36	-	-0.005336	-2.20	0.03	**-0.006253**
Lateral speed	-0.578019	3.42	<0.001	**-0.59846**	-0.360304	8.41	<0.001	**-0.359854**
Weaving position	1.625286	4.79	<0.001	**1.73270**	N/A	N/A	N/A	N/A
Longitudinal range	0.001956	1.13	0.26	-	0.001998	4.94	<0.001	**0.002097**
Lateral range	0.032634	-1.70	0.09	**0.03081**	0.998476	-0.29	0.77	-
Range rate	0.003940	0.22	0.83	-	0.004314	0.69	0.49	-

Same with the results for weaving towards an exit, the Kaplan-Meier survival curves shown in Figure 7 indicated that at one second before a true weaving event (between 4 and 5 s), more than 80% of the data were classified as not initiating a weaving, which was. At 5 seconds before a true weaving maneuver (between 0 and 1 s), 100% of the event had no weaving predicted to begin. The non-weaving probability began to reduce at 4 seconds before the true weaving, which would reduce the model performance.

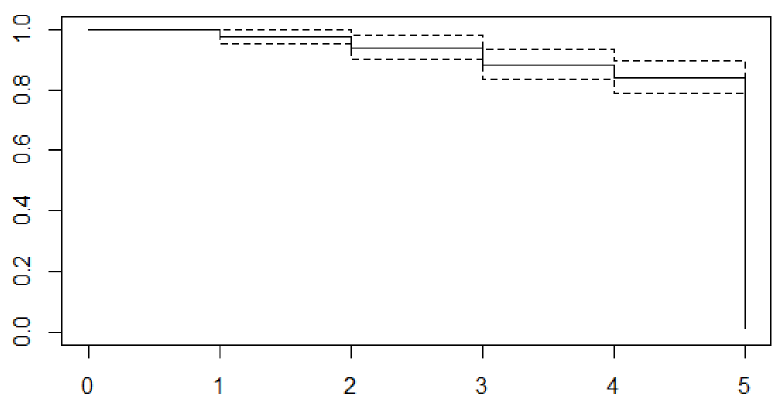

Figure 7. Kaplan-Meier survival curve with 95% confidence intervals for weaving towards an entrance

3.2.2 Decision classification and performance

The ROC curve is shown in Figure 8, with AUC of 0.88, which was a bit lower than the classification for weaving towards an exit and consistent to the findings from the Kaplan-Meier curve. The confusion matrix for the classification models is shown in Table 6 with the information of actual observations and predictions. It was found that the model could identify 83% of the presence of weaving (TPR) and 80% of the absence of weaving (TNR), with the accuracy of 81%. Again, with FPR as 19% and FNR as 17%, the classification missed fewer weaving events, but also led to more false alarms. Although the cost of missing an entrance ramp and colliding with other vehicles if a lane change was triggered at inappropriate time (false alarm) was assumed to be the same, it seemed like a false alarm would be more severe since the traffic speed in the adjacent lane was faster than that towards an exit ramp.

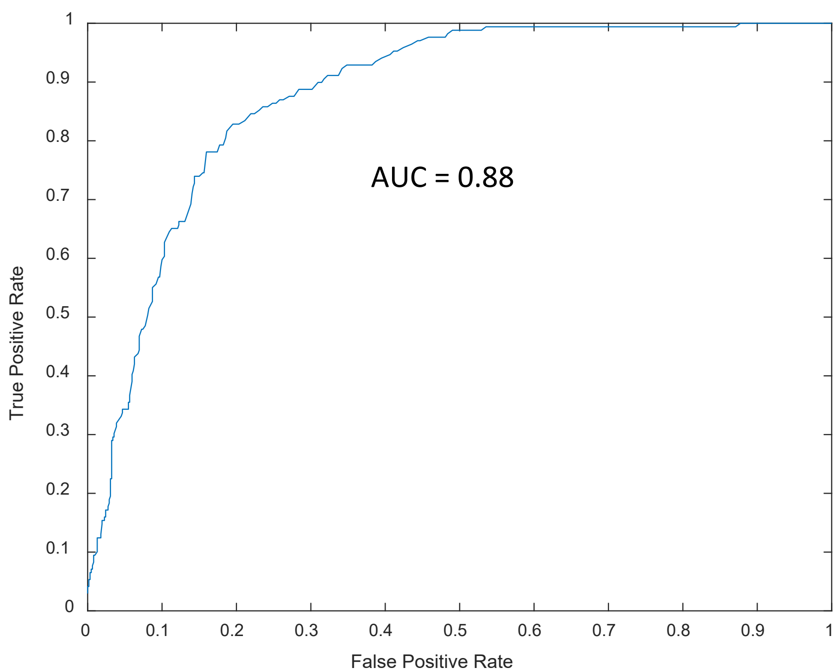

Figure 8. ROC curve for weaving decision classification when taking a highway entrance

Table 6. Confusion matrix for weaving decision classification when taking a highway entrance

Total observations = 789		**Predicted**	
		Lane change	No lane change
Actual	Lane change	140	29
	No lane change	121	499

3.3 Findings from Model Evaluation with Computer Simulation

A computer simulation with Simulink programming environment based on MATLAB. In the simulation scene, an AV and a POV were included, for an AV to engage a weaving task towards an exit or entrance. Figure 9 shows that an AV (white car) had initiated a weaving maneuver towards the exit ramp while a POV (yellow car) drove in the auxiliary lane. In this example, AV began a lane change before POV did due to the initiation suggested by the model. As mentioned in Section 2.5, each AV/POV speed combination would be simulated for 100 times and the performance on average would be reviewed in the following sections.

Figure 9. Simulated scene for approaching a weaving section towards an exit ramp at Mcity

3.3.1 Probability of missing an exit or entrance

Due to limited length of a weaving section, AV might miss the chance for taking an exit or entrance if a weaving initiation was not suggested before reaching the gore point at the end of the weaving section. Table 7 shows the probability of missing an exit ramp under different combinations of AV and POV's speeds. As shown in Table 7, when AV drove with 70 and 75 mph, it might miss an exit ramp if POV drove faster than 50 mph because the range rate to POV did not decrease sufficiently. For such cases, AV remained in the ego lane with the assigned speed and might be run into by POV that was not controlled by any model. The collision with POV would be analyzed in the next section. Note that for the scenario of entering the highway, weaving decision was suggested under all speed combinations and no misses were found, which could cause collisions.

Table 7. Probability of missing an exit ramp

Weaving	**AV Speed (mph)**

towards Exit		20	25	30	35	40	45	50	55	60	65	70	75
POV Speed (mph)	20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	30	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	35	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	40	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	45	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	50	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	55	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.5**
	60	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.1**	**0.9**
	65	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.1**	**1.0**
	70	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**
	75	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**0.5**

3.3.2 Probability of collision with POV

Table 8 and Table 9 show the probability of collision under the different combinations of AV and POV's speeds. As shown in Table 8 and Table 9, all the collisions were found at the diagonal, which meant that AV and POV were driving with the same speed. With different speeds, no collision was found, although the gap in between could be very short. The probability increased as driving with a faster speed and the collision would certainly occur if the speed reached to 50 mph or higher and a weaving was suggested.

Table 8. Probability of collision when weaving towards an exit ramp

Weaving towards Exit		AV Speed (mph)											
		20	25	30	35	40	45	50	55	60	65	70	75
POV Speed (mph)	20	**0.4**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	25	0.0	**0.7**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	30	0.0	0.0	**0.7**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	35	0.0	0.0	0.0	**0.7**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	40	0.0	0.0	0.0	0.0	**0.9**	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	45	0.0	0.0	0.0	0.0	0.0	**0.9**	0.0	0.0	0.0	0.0	0.0	0.0
	50	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**	0.0	0.0	0.0	0.0	0.0
	55	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**	0.0	0.0	0.0	0.0
	60	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**	0.0	0.0	0.0
	65	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**	0.0	0.0
	70	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**	0.0
	75	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**

Table 9. Probability of collision when weaving towards an entrance

Weaving towards Entrance		**AV Speed (mph)**											
		20	**25**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**75**
POV Speed (mph)	**20**	**0.4**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	25	0.0	**0.4**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	30	0.0	0.0	**0.7**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	35	0.0	0.0	0.0	**0.8**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	40	0.0	0.0	0.0	0.0	**0.9**	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	45	0.0	0.0	0.0	0.0	0.0	**0.8**	0.0	0.0	0.0	0.0	0.0	0.0
	50	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**	0.0	0.0	0.0	0.0	0.0
	55	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**	0.0	0.0	0.0	0.0
	60	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**	0.0	0.0	0.0
	65	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**	0.0	0.0
	70	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**	0.0
	75	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**1.0**

3.3.3 Minimum gap between AV and POV

Table 10 and Table 11 show the minimum gap between AV and POV under the different combinations of their speeds. The minimum gap on average was shorter than a vehicle length, which indicated a collision, if AV and POV drove with the same speed (see Table 10 and Table 11). Same results were found from the previous section, but it was noteworthy that with 5 mph as the speed difference between AV and POV, the gap in between could be shorter than the length of two vehicles. Such a short gap was not common for discretionary lane changes but could be possible in weaving sections because drivers did not want to miss the exit/entrance.

Table 10. Minimum gap (m) between AV and POV in the weaving section towards an exit

Weaving towards Exit		**AV Speed (mph)**											
		20	**25**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**75**
POV Speed (mph)	**20**	**5**	16	25	32	38	42	45	48	51	53	55	56
	25	19	**3**	14	22	29	34	38	42	45	47	50	51
	30	36	15	**3**	13	20	26	31	35	39	42	44	46
	35	54	29	13	**3**	11	18	24	28	32	36	39	41
	40	70	43	24	11	**2**	11	17	22	26	30	34	36
	45	86	58	36	21	10	**2**	10	15	20	25	28	31
	50	101	71	48	31	19	9	**2**	9	14	19	23	26
	55	116	84	59	42	27	17	9	**2**	9	13	18	21
	60	132	96	71	51	36	24	15	8	**1**	8	13	17
	65	148	107	83	61	45	32	22	14	8	**1**	8	12

	70	164	120	92	72	54	41	29	20	13	7	**1**	8
	75	180	132	102	82	63	48	37	27	19	12	7	**1**

Table 11. Minimum gap (m) between AV and POV in the weaving section towards an entrance

Weaving towards Entrance		**AV Speed (mph)**											
		20	**25**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**75**
POV Speed (mph)	**20**	**5**	15	25	31	37	41	44	47	50	52	54	55
	25	18	**4**	13	21	27	33	37	40	44	46	48	50
	30	37	16	**3**	12	19	25	30	34	37	41	43	45
	35	54	30	13	**2**	11	17	22	27	31	35	38	41
	40	72	44	25	12	**2**	10	16	21	25	29	33	35
	45	88	58	36	22	11	**2**	9	14	19	24	27	30
	50	102	72	49	32	19	10	**2**	8	13	18	22	26
	55	117	85	60	42	28	18	9	**1**	8	13	17	21
	60	135	97	72	52	37	25	16	9	**1**	8	12	16
	65	149	108	84	62	46	33	23	15	8	**1**	7	11
	70	168	122	93	73	55	41	30	21	14	8	**1**	7
	75	183	134	103	83	64	49	37	28	20	13	8	**1**

3.3.4 Lateral speed as changing lanes

Table 12 and Table 13 show the lateral speed as PV changed lanes under the different combinations of AV and POV's speeds. To successfully change lanes and weave with POV, AV would need to initiate the lane changes with different lateral speeds. POV's speed did not have obvious impact on AV's lateral speed. However, the faster AV drove, the greater lateral speed AV should engage to avoid missing the exit/entrance, as shown in Table 12 and Table 13.

Table 12. Lateral speed (m/s) of AV when weaving towards an exit

Weaving towards Exit		AV Speed (mph)											
		20	25	30	35	40	45	50	55	60	65	70	75
POV Speed (mph)	20	0.1	0.1	0.1	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.4	0.4
	25	0.1	0.1	0.1	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.4	0.4
	30	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.4	0.4
	35	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.4	0.4
	40	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.4	0.4
	45	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4
	50	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4
	55	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4
	60	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4
	65	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4
	70	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4
	75	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.4	0.4

Table 13. Lateral speed (m/s) of AV when weaving towards an entrance

Weaving towards Enter		AV Speed (mph)											
		20	25	30	35	40	45	50	55	60	65	70	75
POV Speed (mph)	20	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	25	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	30	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	35	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	40	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	45	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	50	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	55	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	60	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	65	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	70	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4
	75	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.4	0.4	0.4

3.4 Augmented Reality Demonstration

This demonstration combined the trajectories of the real AV and emulated POV. Since AV did not really detect POV in the real world but relied on the simulated signals for POV positions, the scene for POV was generated by Simulink as the environment of augmented reality, which was a ‘ghost’ POV. A video that showed the lane changes engaged by AV and weaving with POV have been uploaded to the University of Michigan Deep Blue Repositories. Two snapshots from the demonstrative video are shown in Figure 10, while Figure 10a shows that POV just crossed the lane marker to change lanes and Figure 10b shows that AV began the lane change when POV just completely crossed the lane boundary.

(a)

(b)

Figure 10. Snapshot for weaving demonstration in the environment of augmented reality

4. DISCUSSION AND CONCLUSIONS

In this research, a naturalistic driving dataset was mined to develop two automated lane change decision models for the scenarios of taking an exit ramp and entering a freeway. The prediction models performed with the accuracy of 81% or higher and could differentiate more than 83% of the data as an appropriate time to initiate a weaving maneuver.

Although the model evaluations showed that collisions might be observed, those were all under certain conditions while AV and POV maintained the same speed. Besides potential collisions, the ego vehicle would possibly decide not to engage a lane change before reaching the end of the weaving section if the driving speed was greater than 70 mph and the other vehicle with 55 mph or higher. Compared to discretionary lane changes on the freeways, the length of the weaving sections forced AV to respond to POV's maneuver in limited time and driving with a faster speed shortened the duration. In addition, smaller range rate (AV and POV drove with similar speeds) would worsen the situation and AV needed to take additional side collision avoidance actions. This was why the model suggested AV with greater lateral speed when changing lanes that could reduce the lane change duration. However, without operating the longitudinal speed, which was not in the scope of this research, risk of collision was not avoidable.

Although the results of the evaluation showed that these decision models did not lead to a collision-free weaving maneuver, useful insights were provided that both the weaving decision and speed adjustment should be included in a single model. The research team plans to install the modified algorithms to Mcity's new DriveByWire Path Following function and conduct the next round of model validation study.

5. RECOMMENDATIONS

This study serves as an exploration process for the development and evaluation of freeway weaving decision-support functions. The model implementation to an autonomous vehicle was demonstrated, in the augmented reality environment, though. Several recommendations from the research team are as follows.

Vehicle-to-vehicle (V2V) connected environment will be recommended to conduct the follow-on studies that can provide more accurate positions of all the road users. Existing naturalistic driving datasets contain less reliable detection for POV located in the adjacent lane behind the AV. Also, for freeway weaving maneuver, ACM could serve as a better location due to higher speed limits and its variety on freeway infrastructures.

The research team also learned that it was very important to validate the models with computer simulations before conducting any field test with potential risk of collisions. Without zero or minimum risk of collision, no field test should be engaged.

6. OUTPUTS

The outputs shown as below were created during the performance of this research.

- Presentation at CCAT Review on June 16th, 2022
- Presentation at the UMTRI tour for the Network for Employers for Traffic Safety (NETS) Conference on October 7th, 2022
- Presentation at Mcity Connected and Automated Vehicle Working Group Meeting on October 18th, 2022
- Weaving demonstration video for augmented reality (UM Deep Blue Repositories)

7. OUTCOMES

Drawing from the outputs and the naturalistic driving data utilized in this research, our team has begun a follow-up study with Toyota InfoTech Labs (ITL) to investigate driver responses to the behaviors of other vehicles, such as changing lanes, weaving, and tailgating.

8. IMPACTS

The weaving models we developed significantly impact AV developers aiming to create driver-centered technology. This technology will support decision-making in high-speed environments where weaving is common. Another impact for automotive OEM is that the model implementation shows the possibility and Mcity's capability for serving as a platform to test future AV algorithms to perform different tasks on the roads. Additionally, our insights could offer valuable recommendations to government agencies looking to improve the infrastructure design of sections prone to weaving.

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