Analysis and Classification of Driver Behavior using In-Vehicle CAN-Bus Information

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ABSTRACT

This paper describes recent advances in the analysis and classification of driver behavior in actual driving scenarios. We employ data obtained from the UTDrive corpus to model driving behavior and to detect if distraction due to secondary tasks is present. Hidden Markov Models (HMMs) are used to capture the sequence of driving characteristics acquired from the vehicle's CAN-Bus (Controller Area Network) information. Driver behavior is described and modeled using data from steering wheel angle, brake status, acceleration status, and vehicle speed. We evaluate data and models in three distinct classification tasks: 1) action classification, 2) distraction detection, and 3) driver identification. The aim of action classification is to categorize long-term driving behaviors such as turning, lane changing, stopping, and constant/no change (neutral driving). The goal of driver identification task is to classify drivers from their driving behavior characteristics, and distraction detection identifies whether the driver is under distraction due to secondary tasks. Experiments were conducted using 9 drivers from the UTDrive corpus. We report accuracy on modeling driver behavior based on these studies and discuss our future work. Initial results show that event detection for driving can be accomplished at rates ranging from 30-70% depending on the number of unique conditions based on CAN-Bus signals.

1. INTRODUCTION

In 2005, more than 43,000 people died in vehicle crashes in the U.S.A. according to the National Highway Traffic Safety Administration (NHTSA). In addition, NHTSA estimates that 20-30% (1.2 million accidents) of all motor vehicle crashes are caused by driver distraction (using cell phones, eating, drinking, entering data into navigation system, etc.)[1]. Today, the solution to reducing accidents from driver distraction are to introduce laws that prohibit using cell phone and text messaging while driving. However, as the number and complexity of in-vehicle information and entertainment systems increase, these restriction laws cannot stop drivers from performing secondary tasks. Moreover, such laws would have negative effects on the development of new technologies for the car. An alternative to instituting additional laws is the development of a Smart Car System. If such a system is built into the car, the car can detect if drivers are distracted due to secondary tasks. Moreover, the system would conduct specific reactions such as slowing down the car's velocity and alerting the driver. Recent research activities focused on driver behavior modeling such as analysis and modeling of personality with a Gaussian Mixture Model (GMM) framework with driving behavior signals (e.g., following distance, vehicle speed) [3], and modeling and prediction of human behavior employing a set of dynamic models sequenced together by a Markov chain with driving signals (e.g., steering-wheel angle, brake position, and accelerator position) [4] show great promise.

In this paper, we focus on the analysis and classification of driver behavior in actual driving environment using CAN-Bus information. In particular, driver behavior models are trained and used for classifying driving actions, detecting distractions, and identifying driver identity. The driving data from 9 drivers were used in our study. Each driver data was segmented into individual long-term behaviors (e.g., turning, lane changing) and distraction tasks (e.g., tuning a radio, interacting with an automatic voice portal), in order to analyze the characteristics of each driving behavior. In addition, two-dimensional plots show the relationship of two significant signals that represent driver behaviors. Finally, we conducted 3 separate classification experiments: action classification, distracting detection, and driver identification using HMM and GMM topology. After the completion of all of these processes, we found that an HMM framework could be used to effectively detect and classify driver behavior. Ultimately, the application of this study can enhance the safety of drivers on the road. Also, the outcome of the study can coexist with other new technology such as navigation systems and entertainment systems, without restricting drivers use of these technologies and systems.

In our work, the driving data is a subset of the UTDrive corpus. The UTDrive corpus consists of rich multimodal driving data synchronously acquired in actual driving environment. The recording data are two video streams (driver face and front view of vehicle), audio streams from a five-channel microphone array and a close-talk microphone array, brake and gas pedal pressure sensors, following distance, CAN-Bus information (steering-wheel angle, vehicle speed, engine speed, and brake position), and GPS information. Each driver drives along two assigned routes twice: the first drive is neutral or neutral driving and the drive is driving with assigned distraction tasks. In this paper, we focus on the four driving signals obtained from the CAN-Bus information. These signals are sampled at 100 Hz.

The remainder of this paper is organized as follows. Section 2 describes the data analysis of long-term behavior and distracted driving compared to the non-distracted (neutral) driving. Section 3 is devoted to driver modeling based on GMM and HMM with applications on action classification, distraction detection, and driver identification. Section 4 concentrates on the accuracy of each GMM and HMM model. Finally, Section 5 concludes the paper with a summary and directions for future work.

2. DATA ANALYSIS

The first step of utilizing a rich multimodal corpus is a well-defined transcription protocol. Therefore, we designed a multi-modal data transcription framework, and transcribed data based on driver activities (e.g., making a left turn, talking with assistant) according to the reference labels in Table 1.

Table 1: Reference Transcription Protocol

Tasks		Start point		End Point	
Code	Description	Data type	Action	Data type	Action
TL	Turn Left	S	W	D	D>0
TR	Turn Right	D	W	D	D>0
LR	Lane Change Right	Video	A	Video	B
LL	Lane Change Left	Video	A	Video	B
ST	Stop	S	S=0	S	S>0
CT	Call a voice portal	Audio	X	Video	Y
CR	Control Radio	Audio	X	Video	Y
CW	Control window	Audio	X	Video	Y
TA	Talk with an assistant	Audio	X	Audio	Y
CM	Common Task	Audio	X	Video	Y
FR	Free-style Driving	·	O.W	·	O.W

A: When driver starts to glance at the rear mirror
B: When vehicle becomes parallel to the lane.
S: Vehicle speed
D: Steering Degree
W: When steering degree starts to increase
X: When instruction is given.
Y: When driver finishes action
O.W: Otherwise

In order to assess driver-behavior characteristics and to measure the correlation between driving behaviors, we used MATLAB to analyze the data and to generate comparison plots (both one-dimensional and two-dimensional plots). There are five activities considered as distraction tasks during driving: calling a voice portal, controlling radio, controlling the window, talking with an assistant, and performing some common Tasks. There are six long-term driving behaviors: Turn Left, Turn Right, Lane Change Right, Lane Change Left, Stop, and neutral driving. Figure 1 illustrates the four driving signals extracted from the CAN-Bus information: steering wheel degree, brake value, acceleration RPM, and vehicle speed.

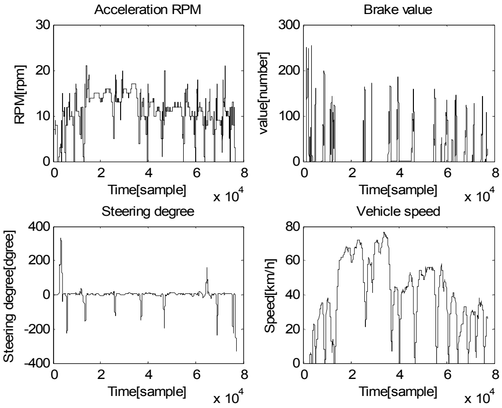

Figure 1: Four Can-Bus signals

First, we analyzed the characteristics of driver behavior under distraction and non-distraction (neutral). Figure 2 compares vehicle speed of neutral driving and driving while interacting with a voice portal using the same vehicle route twice. As we can see, when a driver drives in his neutral mode, the average vehicle speed is 69.91 km/h. The vehicle speed was decreased to 63.92 km/h when the driver used the speech-interface system. We conjecture that the driver slowed down the vehicle speed to increase his safety margin.

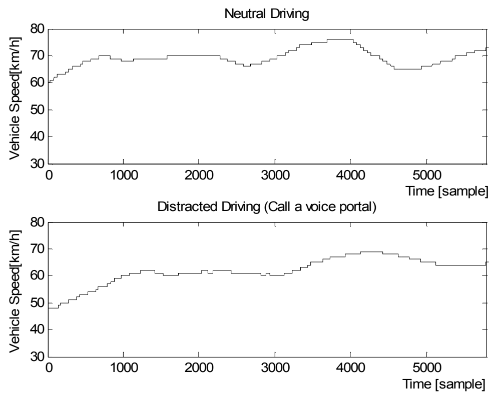

Figure 2: Comparison of vehicle speed for neutral driving and under distraction

Similarly, Table 2 shows the comparison between neutral driving and distracted driving from the same route. The first distraction is controlling and tuning a radio, and the second distraction is interacting with a voice portal. The average speed varies among drivers, with the average speed of 41.08 km/h during neutral driving. The average speed was 34.5 km/h when controlling a radio as the distraction. On another route, the average vehicle speed of distracted driving, calling a voice portal was 64.55 km/h, compared to the average vehicle speed of 68.52 km/h under neutral driving. Therefore, we note that the average vehicle speed of distracted driving is lower than neutral driving for the same route and driving conditions.

Table 2: Average Speed between Neutral driving and Distraction Driving (Control radio and Call a voice portal)

Driver	1	2	3	4	Total average
Neutral driving[km/h]	37.14	32.47	44.79	49.91	41.08
Control radio[km/h]	24.49	28.78	35.94	48.78	34.50
Neutral driving[km/h]	69.91	67.59	62.70	73.87	68.52
Call a voice portal [km/h]	63.91	68.11	62.69	63.48	64.55

For example, the steering degree is not smooth and stable, when the driver calls a voice portal, compared to neutral driving. The average speed is slower when he/she drives with some distraction. To compare distraction caused by cell-phone calling while driving, we generated several plots of CAN-Bus signals, as well as two-dimensional scatter plots.

Figure 3 shows plots of steering degree of neutral driving and distracted driving (having conversation with passenger). Even though both data sets were collected along the same route, the driver maneuvered the steering wheel frequently while talking with the passenger. The neutralized short-term variance of the steering degree under neutral driving is 0.27, and 0.82 under distracted driving (with analyzed window length of 300 samples). This significant difference of neutralized variance of steering degree confirmed that the driver had to correct minor lapses in steering degree to maintain lane occupancy. Similarly, Figure 4 compared the steering degree of neutral driving and driving while controlling a radio. The neutralized short-term variance of steering degree under neutral driving condition is 1.21, compared to 1.69 for distracted driving condition.

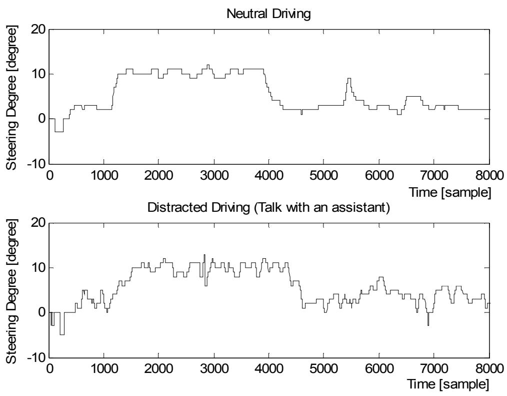

Figure 3: Steering degree versus time for Neutral and Distracted driving (conversation with passenger) along same route conditions.

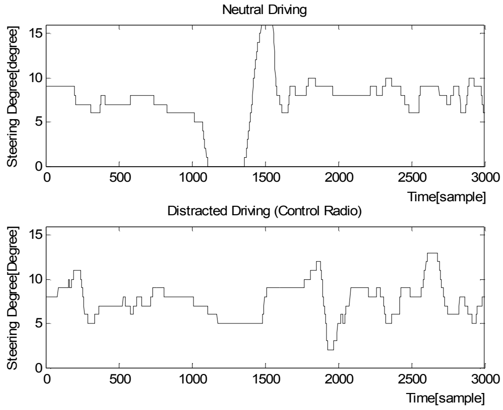

Figure 4: Steering Degree versus time for Neutral and Distracted driving (controlling radio) along same route conditions.

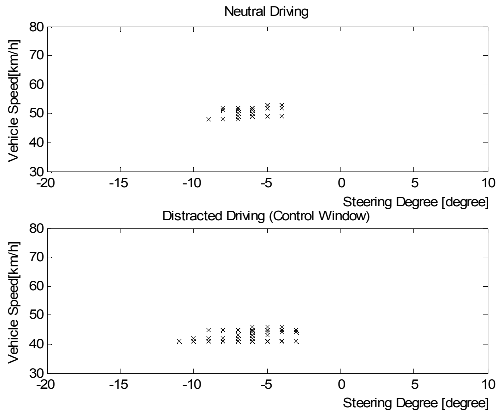

Figure 5: Comparison between Neutral and Distracted driving using vehicle speed and steering wheel angle.

Figure 5 shows the scatter plot correlation of steering wheel angle and vehicle speed. If a driver cannot focus on driving, a wider range of steering angle would occur due to slight corrections in vehicle lateral position, as well as speed reduction to make up for the reduced attention to the road. Under neutral driving condition, the average vehicle speed was 48 km/h and under distraction talk (driver controlled the windows while driving), the average vehicle speed was 41 km/h. Also, the average steering wheel angle for neutral driving was -9^o, and was -11^o for the task of controlling the window. Moreover, the neutralized short-term variance of steering wheel angle for neutral driving is 9.79, and increases to 33.41 for distracted driving (controlling window). The neutralized short-term variance of vehicle speed for neutral driving is 12.38 and for controlling the window is 6.56. These values show that the driver maneuvered the steering wheel more frequently, but he did not change the vehicle speed as much as neutral driving while controlling the window. The correlation coefficient between steering degree and vehicle speed under neutral driving is 0.3044, compared to 0.043 under distracted driving when controlling the window.

Figure 6 shows the dynamic movement of steering-wheel degree for right turning and left turning at the same corners from different drivers.

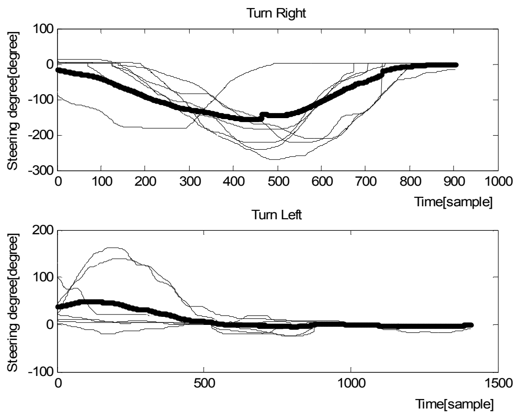

Figure 6: Steering-wheel degree of right turning and left turning from different drivers and their average plots.

The drivers' own characteristics can be classified based on the relationship between vehicle speed and steering wheel angle. In Figure 7, driving behavior signals of three drivers (vehicle speed and steering wheel degree) were mapped onto two-dimensional plots. Both plots from the neutral driving (left) and distracted driving (right) of each driver have analogous patterns. In this figure, the negative value of steering degree represents clock-wise maneuver, and the mesh at the right-side of the column in each plot represents the characteristic of each driver while turning left. The patterns of mesh at the left-side of the column show that driver1 and 2 changed their steering wheel degree faster than driver 3 while turning right. The magnitude of the column in the middle of the plots represents the maximum vehicle speed while driving on the straight road. The longest column in the second plot means that driver 2 drove fastest among three drivers.

3. CLASSIFICATION FRAMEWORKS

In this section, we discuss our driver behavior modeling and classification applications. Here, we employ two statistical modeling frameworks to model driver behavior.

3.1 *Hidden Markov Model (HMM)* is a statistical model in which the system being modeled is assumed to be a Markov process with unknown parameters, and the challenge is to determine the hidden parameters from the observable parameters [5]. An HMM is capable of capture the dynamic movement of a time series.

3.2 *Gaussian Mixture Model (GMM)* is a parametric approach to density estimation [6]. Gaussian mixtures are known for their ability to generate arbitrarily shaped densities. GMMs are used to model driver characteristics.

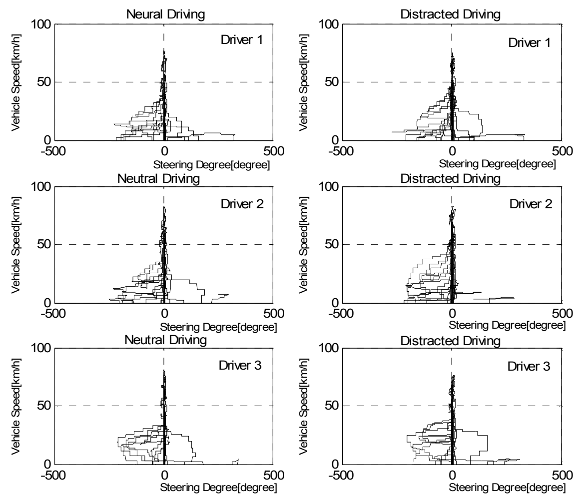

Figure 7: Relationship between vehicle speed and steering-wheel degree of 3 drivers (left: neutral, right: distracted).

3.3 Experimental setup

For driving action classification, six classes are considered: turning right (TR), turning left (TL), lane change right (LR), lane change left (LL), stop (ST) and free-style driving (FR). For training these models, the experiments were conducted with the various numbers of Gaussian components and states to achieve the optimal average accuracy. Here, 70% of each data set was used to train the models and the remaining 30% of the data was used in the evaluation stage.

The next experiment is distraction detection. When we collected the driving data, there were two driving modes, one is the neutral driving, and other is driving with distraction tasks, such as calling on a cell-phone to interact with a voice portal (CT), controlling radio (CR), controlling window (CW), performing some common tasks (CM), and talking with assistant or passenger (TA). Two models were trained with the various numbers of Gaussian components and numbers of states. When we generated a model for distracted driving, the original data sizes varied widely. To make a more accurate model, we segmented the signals of neutral driving into smaller portions of 5 seconds and 10 seconds (close to the period of the other activities). Again, the training models are generated from a random selection of 70% of the neutral driving and distraction signals. The remaining data from these signals is used to test the models.

For driver identification, driving signals are also used to generate models to identify drivers. From analysis of the signals of each driver show that both neutral driving and distracted driving of each driver have its own characteristics, we did not consider the differences between neutral driving and distracted driving to classify driver identity. Seventy percent of driving signals was used for training driver models; the remaining was used for test models. Total six driver models were trained. The number of Gaussian components and states were optimized to achieve the models that provide the highest accuracy.

4. EXPERIMENTAL RESULTS

4.1 Action classification

We generated the action (activity) models by using four-dimensional CAN-Bus signals, based on the HMM topology. There are six action models: turning right (TR), turning left (TL), lane change right (LR), lane change left (LL), stop (ST) and neutral driving (FR). Figure 8 shows the accuracy of action classification with different numbers of Gaussian components and HMM states. The optimal point is at two Gaussian components and eight states. The average accuracy is 69% (chance is 16.67%). Table 3 shows classification accuracy for each action class.

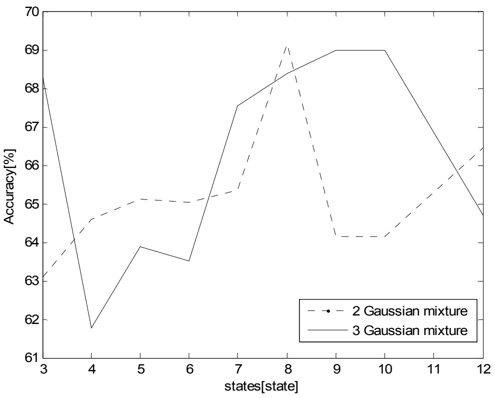

Figure 8: Average accuracy of driver Action Classification across 6 Driver Actions

Table 3: Accuracy of Driver Action Classification

Activities	TR	TL	LR	LL	ST	FR
Accuracy (%)	93.54	100	48	44.44	83.33	45.62

4.2 Distraction Detection

Table 4 shows the EER (Equal Error Rate) of distraction detection task with HMM parameters of 3 Gaussian mixtures and five states (M3S5), four Gaussian mixtures and six states (M4S6), and six Gaussian mixtures and six states (M6S6). These numbers involve a tradeoff between two error types: missed detection and false alarms probabilities. Figure 9 illustrates two example DET (Detection Error Tradeoff) curves [7]. For the DET curve, the closer to the bottom left corner represents better system performance (less errors). From these results, we can conclude that 10 seconds data has better performance than the 5 seconds data. That is, the longer driving data test shows more consistent characteristics of distraction.

Table 4: Equal Error Rate of Distraction Detection Model

	M3S5	M4S6	M6S6
5 sec. Model (%)	41.76	39.17	44.59
10 sec. Model (%)	37.59	36.35	34.29

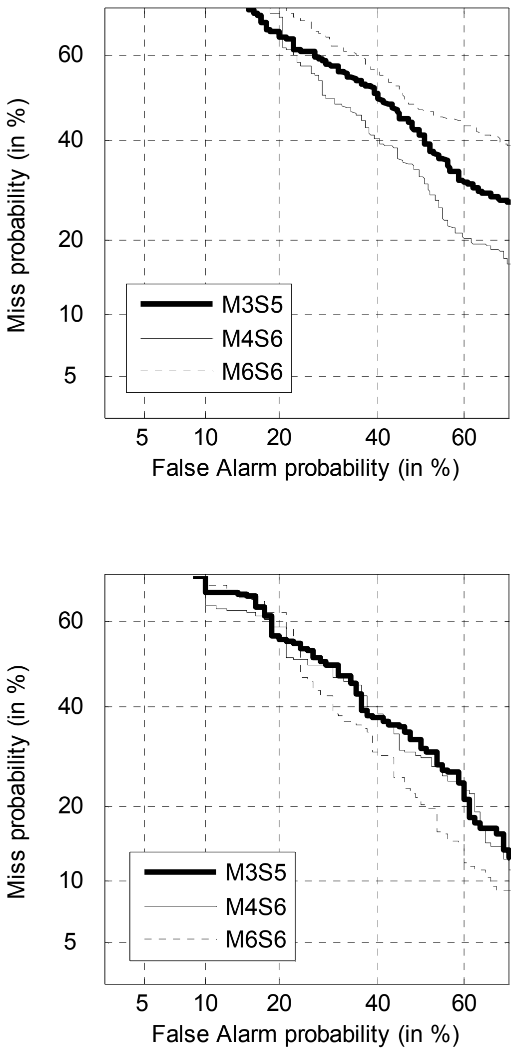

Figure 9: DET Curves for a distraction detection (5 sec. driving duration and 10 sec. driving duration)

4.3 Driver Identification

Figure 10 illustrates the accuracy of HMM model for both segmented signals, 5 and 10 seconds. The first plot shows the accuracy of the GMM in which the number of states is 1. When the number of Gaussian components is 45 and the number of states is 1 (in particular, GMM with 45 mixtures), the models yield the best performance for both driving durations (29.50% for 5 seconds and 29.48% for 10 seconds). The second plot shows the accuracy of the most efficient HMM (HMM with 3 states). When the number of Gaussian components is 7, the models show the best performance (31.45% for 5 seconds and 29.16% for 10 seconds). In the third plot, we fixed the number of Gaussian components and draw the accuracy while changing the number of states. It shows the trajectory of accuracy depending on the number of states. Obviously, HMM using 3 states yields the best performance for both driving durations.

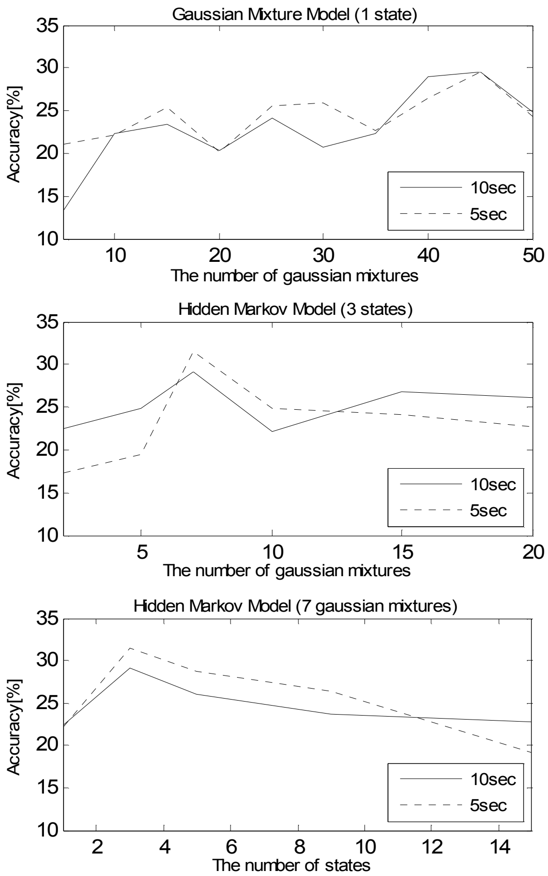

Figure 10: Accuracy of driver identification

5. CONCLUSION

In this paper, driver action classification, driver distraction detection, and driver identification were studied using in-vehicle CAN-Bus signals with both GMM and HMM frameworks. We achieved 69% accuracy for action classification, and 25% accuracy for driver identification. Distraction detection had 35% EER. Data analysis showed that the average vehicle speed is lower under distracted driving, compared to neutral driving. Also distracted driving has a wider neutralized short-term variance than non-distracted (neutral) driving. Our preliminary studies showed some promising results using CAN-Bus signals to model driver behavior, but further studies could explore the consistency for each distraction task, as well as variability for individual subjects.

6. REFERENCE

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