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Impact of Secondary Tasks on Individual Drivers: Not All Drivers Are Created Equally

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ABSTRACT

There has been rapid growth in the mobile-phone industry in terms of technology and growing number of users with migration into the car environment. There is also a significant demand for smart phones capable of accessing email, listening to music, organizing daily activities, linking to social networking sites, while the user is on the move. The automotive industry has been significantly impacted by such mobile-phone usage. Driving a car is a complicated and skillful task requiring attention and focus. However many people perceive driving to be easy - second-to-habit or an extension of their natural skills. This complacency encourages drivers to multitask while driving. While many drivers manage this multitasking comfortably, it becomes a distraction and contributes to increased risk while driving for some. Since the effect of multitasking is variable on different drivers, it is important to understand its impact on individual drivers. This study focuses on assessing the impact of several secondary tasks such as speaking over a hand-held mobile phone, tuning the radio, selecting songs from an MP3/CD playlist, speaking to a co-passenger, on individual drivers. To assess the driver activity, we formulate stochastic models such as Gaussian Mixture Models (GMM) using only CAN-bus signals collected on-road in real world driving situations from the UTDrive corpus. We also categorize drivers based on their distraction level into (1) least impacted, (2) moderately impacted, and (3) most impacted drivers. As the automotive industry further advances in developing active safety systems, such driver centric adaptive systems will help in personalizing the vehicle by triggering active safety systems only when drivers are impacted or when they show tendencies of such impact. This will help motivate drivers to use active safety systems rather than disabling them because they are annoyed.

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INTRODUCTION

Driving is inherently a complicated task involving attention to many details. Drivers primarily control the longitudinal and lateral motion of the vehicle. As a feedback, the driver constantly perceives his relative position on the road with reference to other objects and/or vehicle in the vicinity. This attention seeking primary task is performed mainly using the steering wheel, gas and brake pedals and a reference speed. Though skill and experience level of the driver plays a significant role [1], driving requires careful attention to the changing environment both within and outside the vehicle. With people spending a lot of time in their cars these days, there is a complacency built in many drivers and they take this primary driving task as a natural habit. They try to “do more” during their driving time. An average American spends more than 300 hrs in a vehicle each year [2]. Business, ordering for food, searching for places, exchanging emails, eating, speaking over phone, texting and many more tasks happen on the move in the car environment. Especially with the current advancements in technology and the ready availability of information there are a wide range of infotainment systems available. Using these infotainment devices in the vehicular environment while the person is driving can be termed as secondary tasks and these tasks also require some attention to operate. Many of these tasks require the driver to share his physical, auditory, visual or cognitive abilities while driving. Often, this leads to lack of sufficient attention towards driving and towards the road which could lead to accidents.

The automotive industry acknowledges the needs of today's society. However, they are cautious about these secondary tasks that are performed in the car. Even with the imposition of laws prohibiting the use of infotainment systems in various regions, the number of accidents has not shown a decline. Human error is the main cause for 57% of accidents, and is a contributing factor in 95% of the accidents

[3]. National Highway Traffic Safety Administration (NHTSA) also estimates that driver distraction is the cause for about 1.2 million accidents [2].

Addressing driver inattention, research and automotive industry have designed various systems. Systems such as pedestrian detection, night vision, lane tracking system, forward collision warning help the driver to focus more on the road. Systems like adaptive steering assist, lane keep assist, collision mitigation by braking provide control feedback and help driver adjust better to the driving environment. While these systems already exist and assist drivers, research is in progress to understand the effects of various tasks on driving and how driver behaviors uniquely affect driving performance. Though technologies such as voice interactive systems, navigation systems, hands-free mobile communication have proven to be better than their manual equivalents [4], it is important to understand the impact of adding new infotainment features in the car on the driver's cognitive workload. Understanding and modeling driver behavior could help manage the cognitive workload of the driver. Though this modeling approach is not new [5, 6, 7], automotive researchers have begun to recognize its advantages. Infotainment systems are beginning to use learning algorithms to understand the driver's needs and suggestions are prompted to the driver for easy handling of the system.

It is becoming inevitable for drivers to operate these systems and perform secondary tasks while driving. Even if secondary tasks do not divert the driver's attention and pose a major threat, they still expose drivers to inattention and increased cognitive workload. Early detection of such driver distractions could prove very valuable in taking corrective measures and preventing possible accidents. It is the subject of this paper to analyze the effect of secondary tasks and to identify risky situations when the driver is most vulnerable.

The remainder of the paper is organized as follows - the following section gives a brief insight into the signals used to model driver behavior including how they are acquired and processed. This is followed by our approach towards driver behavior modeling. Finally, results and conclusions are summarized providing insight into the effects of secondary tasks on individual drivers.

SIGNAL ACQUISITION

For the safety of both driver and vehicle, it is important to understand how drivers perform while driving. Environmental conditions, vehicle condition and driver state are important factors which affect driving performance. Various sensors and systems such as sun load sensors (to identify illumination), gyro sensors (for vehicle and road banking), head distance sensors and cameras are used to assess and provide assistance for environmental variations. Sensors also provide monitoring of vehicle conditions and provide control feedback to compensate for any unnecessary vehicle variations.

Similarly, to assessing human behavior and current conditions, various sensors and systems have been used. Sensors such as heart rate variability (HRV), skin conductance (GSC), EEG, ECG and EMG are intrusive but have proven to be useful [8]. In the driving condition it is not practical to use these sensors but can serve as a baseline or ground truth assessment when being compared with other non-intrusive sensors for performance. So, rather than looking at intrusive sensors to analyze driver's condition, the approach used here is to utilize the non-intrusive and already available CAN-bus signals to assess driver activity. CAN-bus signals offer a low cost, reliable and sufficient system and can be readily deployed in real world systems.

CAN-bus Signals - Reliable and Sufficient Source of Information

Over the past few decades, automobiles have transitioned from pure mechanical systems to electromechanical systems with extensive sensors, actuators and embedded systems controlling the core vehicle functionality. Communication between these systems mostly happens via a network called the Controller Area Network (CAN) [9]. The CAN-bus carries critical vehicle/engine related information such as engine temperature, air pressure, fuel monitoring to name a few. Along with these, there are signals such as gas pedal pressure, brake pedal pressure and steering wheel angle which are the driver's primary controls to maneuver the vehicle, and vehicle speed which is the driver's main feedback. Some CAN-bus signals are made available to the outside world through the On-Board Diagnostic (OBD) port. Figure 1 shows the gas and brake pedal pressure, vehicle speed and steering angle information from CAN-bus. It can be clearly seen that initially the driver hits the brake pedal, vehicle speed goes down and then he makes a turn without stopping. Since the main focus of this study is to understand how drivers handle the vehicle while performing secondary tasks, CAN-bus data provides a reliable and sufficient source of information.

A Brief Note on UTDrive Project

To build effective driver dependent systems, developing mathematical models capable of explaining and predicting driver behavior is important. In order to obtain modeling parameters to build driver models, a multimodal data acquisition platform is used to collect data in real traffic conditions. The multimodal database of real world driving data collected is demographically well balanced with a wide range of drivers from different nationalities, age, gender, and levels of driving experience. UTDrive Project [10] was part of a three-year NEDO supported international collaboration between universities in Japan, Italy, Singapore, Turkey, and USA. The UTDrive Project has focused on research that employs multi-modal data for developing a framework for driver behavior modeling and driver-vehicle interactions for safe driving. The data was collected using a Toyota RAV4,

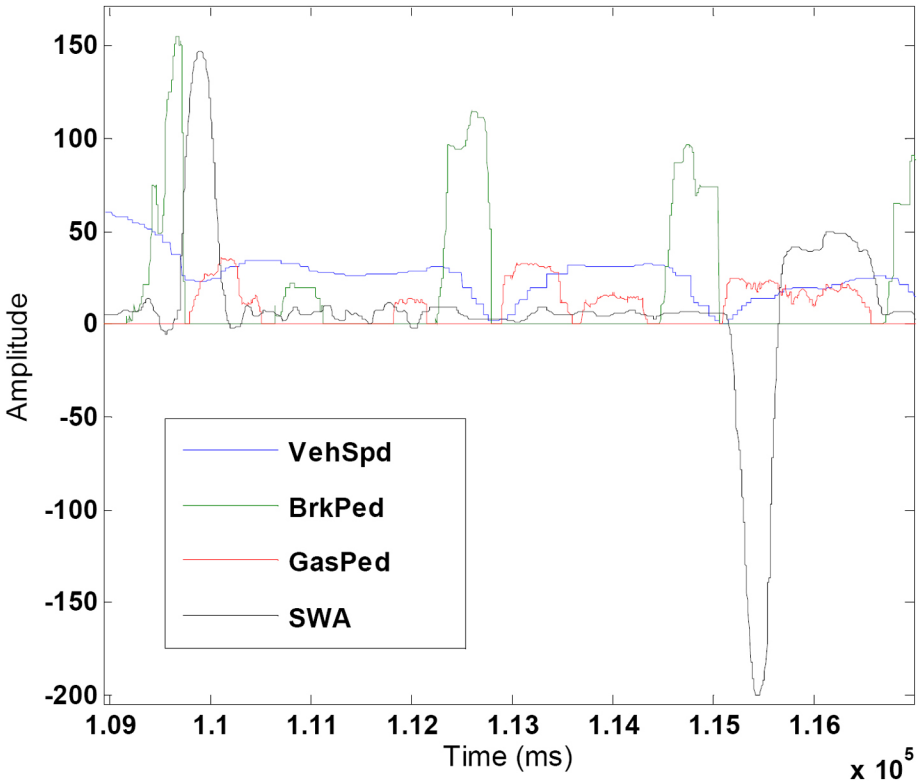

Figure 1. Vehicle CAN-bus signals extracted from OBD-2 port

Figure 2. Instrumented UTDrive data collection vehicle along with the sensors

instrumented with various sensors (i.e., audio, video, gas/ brake pedal pressures, forward distance, GPS information, and CAN-bus signals) as shown in Figure 2.

Data/Route Description

Signals from CAN-bus, such as brake pedal pressure, steering wheel angle and vehicle speed (as seen in Figure 1) are used to model driver behavior. Other sensors including camera and microphone data are used to transcribe CAN-bus data. This data transcription is crucial in developing mathematical models as it labels the driver's actions. This provides the basis for further signal processing and also serves in evaluating results against ground truth. Since real world traffic scenarios and driving are highly dynamic, transcribers process the entire route to label events which occur during driving. Figure 3 shows the multimedia data annotation tool - UTDAT [11] which is used for transcription. Driver activity is labeled using (1) two cameras - one facing the road and another facing the driver, (2) microphone array - listening to in-vehicle conversations and (3) CAN-bus signals - looking at the vehicle dynamics. Feedback is also collected from drivers after every driving session regarding their experience in performing maneuvers and secondary tasks. Segments marked as distracted are re-assessed by other observers to validate it as a distraction.

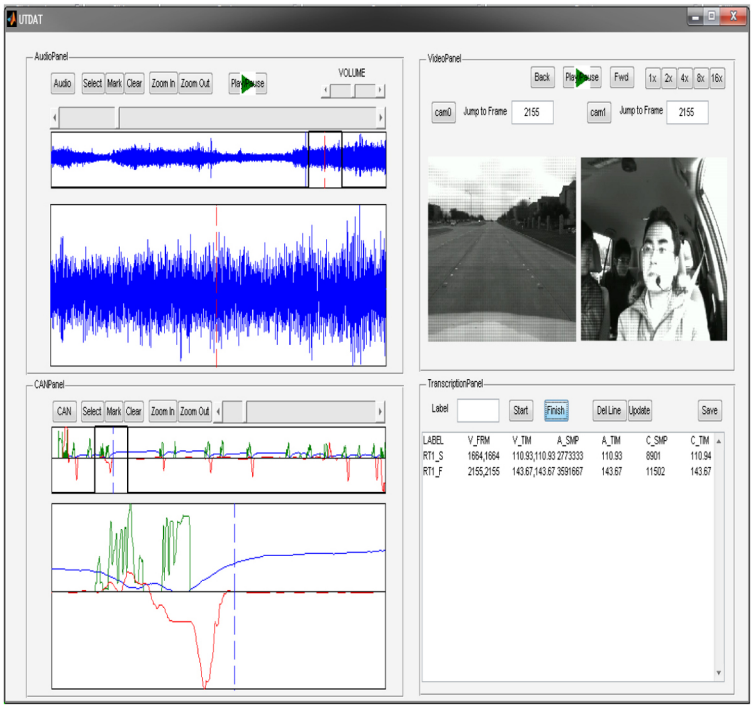

Figure 3. UTDAT- Multi-modal data annotation tool

A small subset of 8 drivers' data (numbered 1 to 8 in no particular order in this paper) from the UTDrive corpus is used in this study. The drivers are made familiar with the route, tasks which would be performed, vehicle and its controls. Each driver is required to drive through the route twice which is shown in Figure 4. In one of the sessions they are not expected to perform any secondary tasks and they drive normally through the route and in the other session, they are expected to perform secondary tasks while driving. The complete route takes approximately 10 minutes to drive and it goes through residential areas and school zone. The secondary tasks performed are - LC (Lane Changing), CO (Conversation with co-passenger), MP (speaking on mobile phone) and CT (Common Tasks). They are labeled (in Figure 4) against each leg of the route where they are performed. Some of the common tasks performed are tuning the radio, selecting a particular song in a music player, adjusting the AC/heater levels, etc. Though lane changing in not a secondary task and a part of normal driving, it has been included in this study to benchmark cognitive loads for secondary tasks versus a typical driving task.

Figure 4. Secondary tasks performed in different legs of the route

DRIVER BEHAVIOR MODELING

Previous works [10, 11, 12, 13] have shown how CAN-bus signals can be used in identifying maneuvers and distraction in those maneuvers. Gaussian mixture models (GMM) have been successfully employed in building driver specific models and to assess neutral and distracted condition of drivers.

A GMM is a statistical model which models the distribution of feature vectors (here they are the salient features from CAN-bus). It estimates a probability density function using the expectation-maximization algorithm [14]. The GMM built for neutral driving comprises the entire space which a normal driving pattern occupies. Hence a raw signal can be scored for its likelihood of being closely represented by either the neutral or distraction model. The well-known Kullback-Leibler (KL) divergence or KL distance, which is a measure of the differences between reference probability distribution P to an arbitrary probability distribution Q [15],

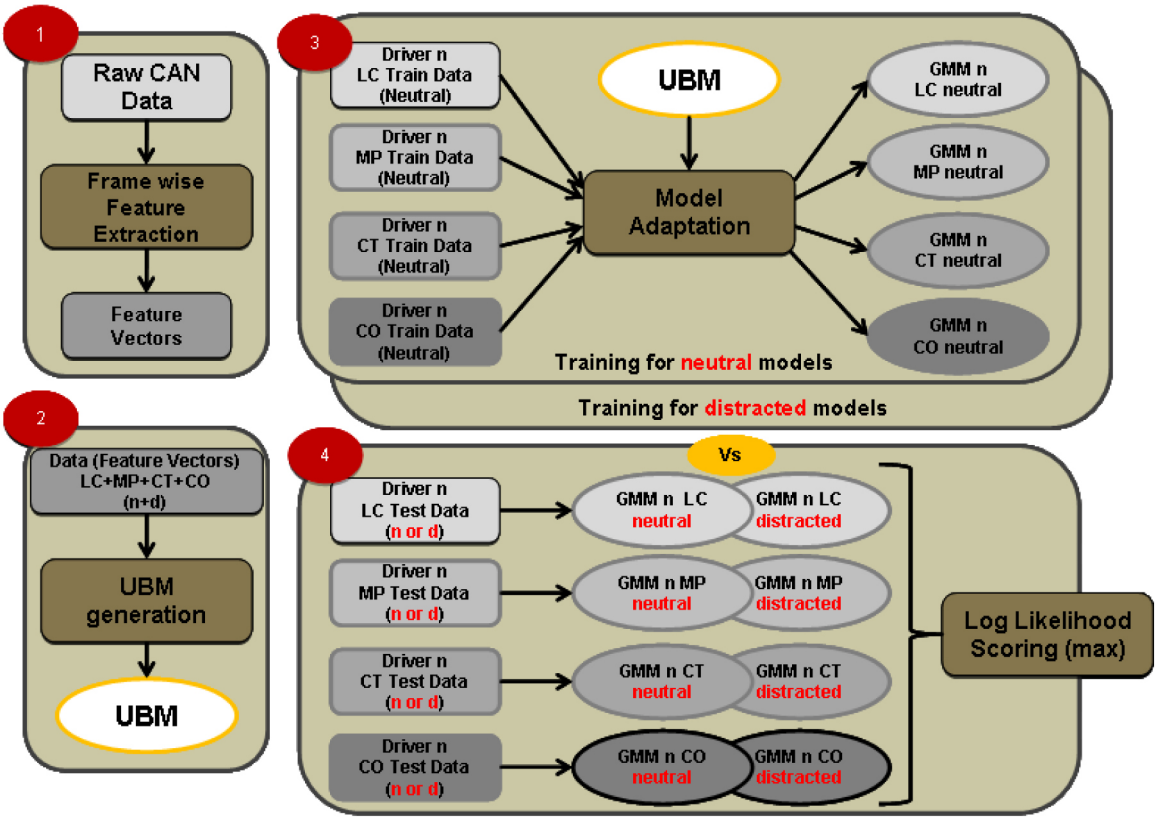

Figure 5. GMM-UBM framework 1) Feature extraction 2) UBM Generation 3) MAP adaptation 4) Maximum Log likelihood scoring

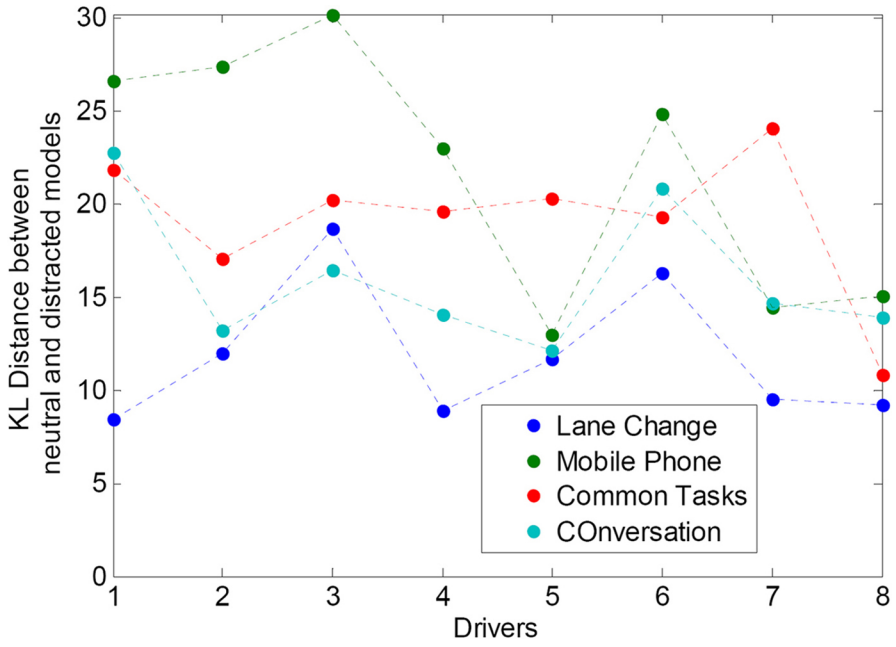

Figure 6. KL-Distance between Neutral and Distracted models

is utilized to assess the distraction level in drivers performing secondary tasks. For discrete probability distributions, p={p1, …, pn} and q={q1, …, qn}, the KL-distance is defined to be

$$KL(p,q) = \sum_i p_i . \log(p_i / q_i)$$

From previous work, it is clear that by using GMMs, it is possible to identify maneuvers and also identify if these maneuvers are executed normally or if the driver was distracted. It is also noted that some drivers are more distracted than others. If some drivers are not distracted by performing secondary tasks, this study tries to understand how their driving differs from those who are distracted while performing the same task. For this, a micro analysis on individual driving pattern is performed by segmenting the tasks into 5 second frames and assessing if that frame is likely to be distracted or neutral driving. The results are analyzed to see if the driver continues to stay distracted or recovers from distraction.

Since the effect of driver variability and driving context should be minimized to assess driver intent and identify distraction detection; the driver dependent GMM-UBM framework is adopted as shown in Figure 5. A detailed description of Gaussian Mixture Models (GMM) and Speaker Recognition can be found in [14]. There are mainly 4 stages in the GMM/UBM framework- (1) feature extraction, (2) universal background model (UBM) generation (development), (3) driver dependent model adaptation (training), and (4) testing as shown in Figure 5. Some salient features such as raw signals of vehicle acceleration, brake pedal pressure, steering wheel angle, vehicle speed, their derivates and standard deviation are extracted from the CAN-bus signals to form feature vectors. A UBM is developed using a large number of drivers' CAN-bus data other than the eight used here for training and test. Two sets of driver dependent GMMs (neutral and distracted) are obtained by MAP adapting the UBM using neutral and distracted driver specific feature vectors. Using log-likelihood scoring, each test data is scored against both GMMs representing neutral and distracted models for a particular driver. Similar to the study in [16], the Kullback-Leibler (KL) distance is computed between neutral and distracted GMMs for every driver and the result is shown in Figure 6. In this case, if the distance of separation is small, the neutral and distracted GMMs do not differ in CAN-bus signal structure. However, if the distances are large, this implies significant changes in the underlying GMM structure for distraction.

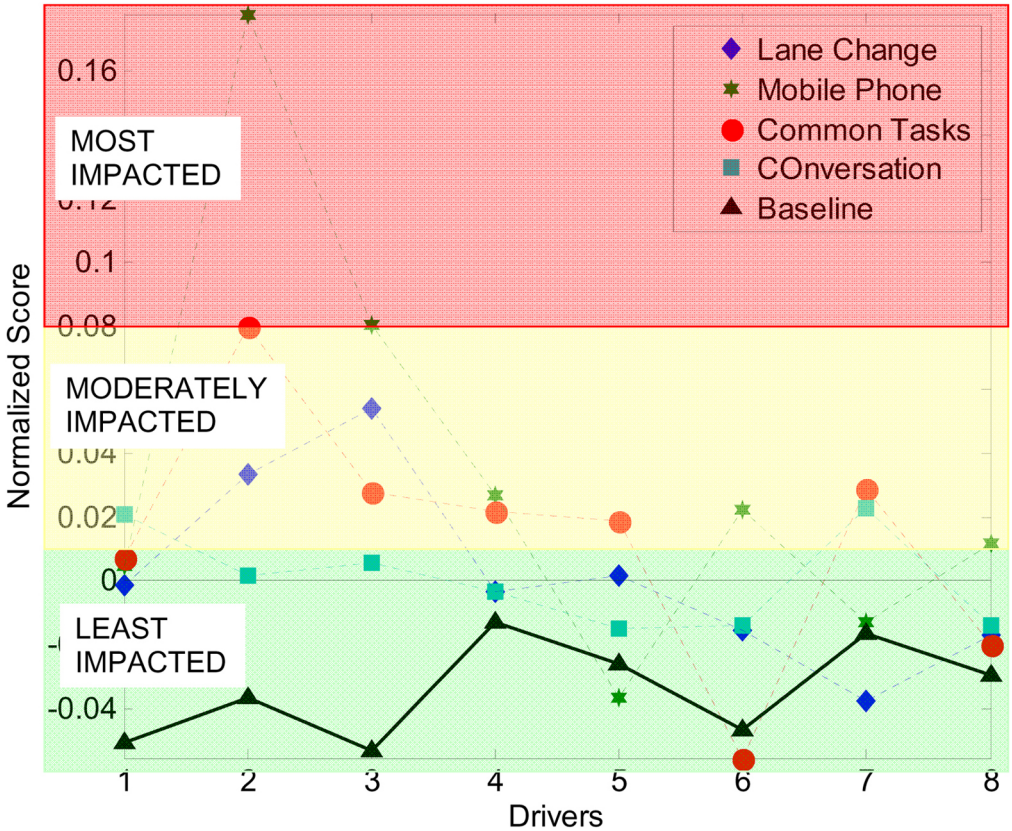

Figure 7. Scores showing the effect of different secondary tasks on individual drivers

RESULTS

To minimize the driver and driving-context variability (road curvature, stop signs etc) driver and task (leg of the route) specific models were built and used for evaluation. The likelihood scores obtained were compared against neutral and distracted models and the driver condition was assessed. To understand the impact of all secondary tasks on individual drivers, the scores are normalized with reference to the distance of separation between models. Figure 7 shows the plot for the effect of different secondary tasks on individual drivers. Negative scores imply that the drivers are not affected by secondary tasks and they are driving normal, the way they do while not performing tasks. The higher the score, it implies that the individual is significantly impacted by the particular secondary task. The black solid line indicates each driver's baseline for normal driving. As can be seen, most of the drivers are not affected by in-vehicle conversation with the co-passenger. However depending on the nature of conversation, it can be seen that conversations move towards moderately impacting most drivers. Driver 4 and 7 have a higher baseline which indicates that they were either not familiar of comfortable with the road/ vehicle or that is their normal driving style. Since they both (D4 and D7) do not show too much variation while performing tasks, they can be considered as bordering between least and moderately impacted due to secondary tasks. For most of the drivers, common tasks and mobile phone conversation was moderately distracting. Since the drivers were familiarized with the vehicle just before data collection, it was distracting to most drivers to find and handle the in-vehicle controls. Also clearly seen is that driver 2 (D2) is the most distracted and most impacted due to secondary tasks.

CONCLUSION

Through this analysis, it was confirmed that not all drivers are affected the same way when performing secondary tasks. While some experience high distraction, still others manage tasks very easily without becoming distracted. Therefore, it is not just the skill or experience level, it is also the familiarity of handling the secondary tasks which plays a significant role in impacting the driver's attention. “Not all drivers are created equally”, it should also be said that “not all drivers should be treated equally”; driver specific systems and adaptive systems should be deployed to better understand and tune to the driver's needs and comfort level. In this way, drivers would benefit more from using active safety systems rather than becoming annoyed and simply disable them.

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