Driver Modeling for Detection & Assessment of Distraction: Examples from the UTDrive testbed

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Vehicle technologies have advanced significantly over the past twenty years, especially with respect to novel in-vehicle systems for route navigation, information access, infotainment, and connected vehicle advancements for vehicle-to-vehicle and vehicle-to-infrastructure connectivity/communications. While there is great interest in migrating to fully automated/self-driving vehicles, a number of factors such as: technology performance and cost barriers, interest in public safety, insurance issues, legal implications, government regulations, etc. all suggest it is more likely to have multi-functional vehicles, which allow for smooth transitions from complete human control towards semi-supervised/assisted, to fully automated. In this regard, next generation vehicles will need to be more active in assessing driver awareness, vehicle capabilities, traffic/environmental settings, and how these come together to determine a collaborative safe and effective driver-vehicle engagement for vehicle operation. This article presents an overview of a range of issues focused on driver modeling for detection and assessment of distraction. Examples from the UTDrive project are used whenever possible, along with comparison with existing research programs. Areas addressed include (i) understanding driver behavior and distraction, (ii) maneuver recognition and distraction analysis, (iii) glance behavior and visual tracking, as well as (iv) mobile platform advancements for in-vehicle data collection and human-machine interface. This study highlights challenges in achieving effective modeling, detection, and assessment of driver distraction using both UTDrive instrumented vehicle data as well as naturalistic driving data.

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1   INTRODUCTION

Over the past few years, there has been a significant effort in establishing "smart cars" that have the capability to achieve self/autonomous driving for their passengers or the passive operator. While great strides in autonomous driving will continue, greater research and understanding is needed regarding driver modeling as we transition from full-driver control to various levels of assistive-through-automated self-driving. The ability for smart cars to seamlessly move back and forth between completely automated, semi-automated, semi-assistive, to no-assist, remains a major challenge. In this study, we consider an overview of the recent advancements in driver modeling to assess driver status, including the detection and assessment of driver distraction when the vehicle is operated in a user-controlled scenario. The recent large-scale data collection undertaken by the United States Transportation Research Board - Strategic Highway Research Program (U.S. TRB: – SHRP2 [1,91]), will provide an enormous (i.e., +2 Petabyte) data set of naturalistic data. The ability for researchers to mine this corpus to develop better models of driver status will offer new insights into next generation smart vehicles, which have the capability of migrating between compete user controlled to full autonomous.

An extensive amount and scope of research/development has been underway by many laboratories in the US, Japan, Germany, Sweden, Korea, and worldwide, and therefore it is not possible to provide an exhaustive coverage of all significant advancements. Instead, the goal here is to provide a representative look at the topic of driver modeling, with specific interests in how advancing technologies impact driver distraction. This includes a range of signal processing technologies related to CAN-Bus (Controller Area Network) analysis, image/video processing, speech/audio for human-machine interaction, and other advancements leading to current and future intelligent assistance in the vehicle. Here, we review past research and development activities from both academic and industrial perspectives that include: (i) Understanding driver behavior and driving distraction, (ii) Maneuver recognition and distraction analysis, (iii) Glance behavior and visual tracking, and (iv) Mobile platform advancements.

The recent IEEE Signal Processing special issue: "Smart Vehicle Technologies: Signal Processing on the Move" [2], considered a range of topics for smart vehicles advancements that included driver-behavior modeling using on-road driving data [3], driver status monitoring systems [4], smart driver monitoring [5], conversational in-vehicle dialog systems [6], active noise control in cars [7], and coordinated autonomous vehicles [8]. In this article, we provide a number of complementary highlights to these excellent overview articles. There have been several experiments/datasets carried out and collected on the driver behavior analysis, such as [9-11]. For the sake of illustration, the UTDrive naturalistic driving dataset, which can be found at [12], has been conducted by CRSS-UTDrive Lab since 2006, with the interest of understanding driver behavior and distraction from multi-channel sensor data (see Fig. 1) [13]. Here, we focus on both current advancements, past efforts, and directions for future research. Examples stemming from the UTDrive project are highlighted as examples, as well as efforts from VTTI (Virginia Tech. Transportation Institute), UMTRI (Univ. of Michigan Transportation Research Institute), UCSD (Univ. of California – San Diego), Europe, Japan, and Korea [14].

The remaining part is organized as follows. Section 2 describes an overall understanding of driver behavior and driving distraction. Section 3 demonstrates the analysis from the driving performance perspective, which is to first identify driving context in term of events/maneuvers, and next compare the variations of distracted driving against normal/safe driving. Section 4 provides a more straightforward approach by monitoring the

driver's visual attention. Section 5 migrates the in-vehicle data collection to a mobile platform, and extends the platform for a less distracted, voice-based human-machine interface.
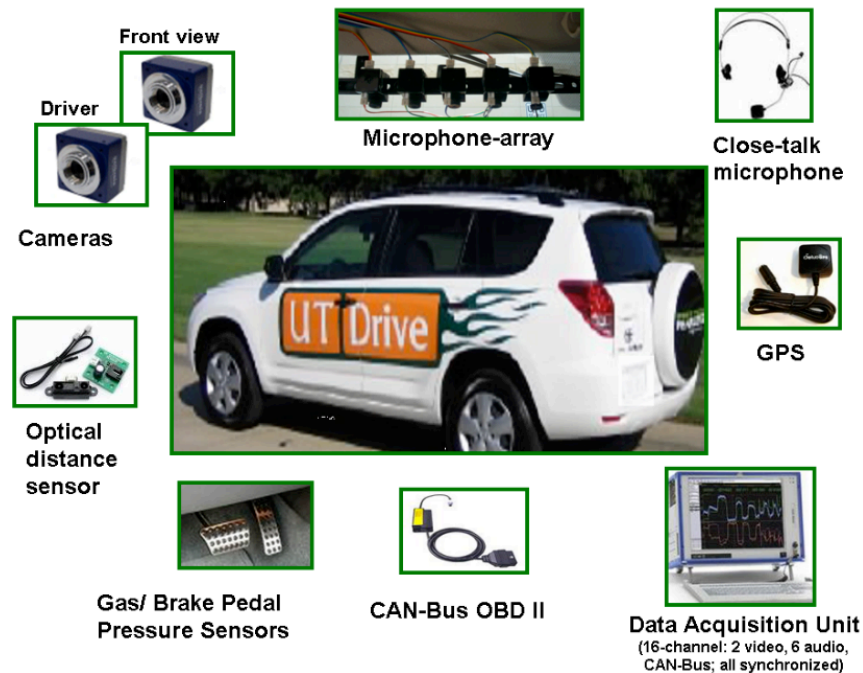

Figure 1: UTDrive experiment testbed – synchronized multi-channel measurements

2   UNDERSTANDING DRIVER BEHAVIOR AND DRIVING DISTRACTION

Driver activities within the vehicle can be broadly classified into primary tasks that are essential for operating and directing the course of a vehicle in a given environment; and secondary tasks that are not essential or related to the primary task of driving. Generally, secondary tasks divert drivers' primary attention of driving and degrade their driving performance. The degradation is directly attributed to the driver (distraction, inattention), the vehicle (condition, familiarity) and/or the surrounding environment (traffic, weather). Both driver distraction and driver inattention are frequently occurring events in the car.

Driver inattention is defined as insufficient or no attention to activities critical for safe driving. Inattention could either be a voluntary or involuntary diversion of attention by the driver [15]. Driver Distraction has been formally defined [16] as - *Anything that delays the recognition of information necessary to safely maintain the lateral and longitudinal control of the vehicle (primary driving task) due to some event, activity, object or person, within or outside the vehicle (agent) that compels or tends to induce the driver's shifting attention away from the fundamental driving task (mechanism) by compromising the driver's auditory, biomechanical, cognitive or visual faculties or combinations thereof (type).*

As suggested in [15, 16], without these formal definitions, cross study comparisons cannot be made and statistics can vary drastically leading to wrong observations. It is important to note that, driver distractions are generally caused by a competing trigger activity that may lead to driver inattention, and in turn degrade driving performance. Alternatively, other forms of driver inattention might not necessarily be due to a trigger or

competing activity, hence making it difficult to detect and even harder to control. By identifying some of the causes of driver distraction, it is possible to isolate scenarios when the cause of distraction can be controlled.

Most secondary tasks are not distracting and do not require complete attention of the driver. However, while executing a complex task such as driving, the majority of the driver's attention is towards a safe drive, and performing a secondary task means sharing limited available human cognitive resources. Some important characteristics related to secondary tasks that distract the driver are - duration of the activity, frequency of the activity, attention required to execute the activity (Attention Demand), ease of returning to primary task of driving, location and time when the activity is executed and individual driver's comfort in executing the task and also in performing multiple tasks. Since visual modality has been well studied, it has been established that diversion of driver's visual focus away from driving task for more than 1.5 sec. distracts the driver [17].

Driver follows road rules, maintains lane and an acceptable gap between surrounding vehicles, while achieving good reaction time to changes such as traffic signs and tail lamps [18]. From the vehicle control side, the driver's primary physical contacts are the steering wheel, gas and brake pedals, seat, and ego vehicle speed as reference. Any secondary task that tends to distract the driver, has a direct influence on body movements that manifest in control of the vehicle. Hence, change in driving performance can be evaluated by analyzing these signals. Each driver has a comfortable way in which he/she interacts with the vehicle, and analyzing these signals can help build a driver behavior and characteristic model.

3   MANEUVER RECOGNITION AND DISTRACTION ANALYSIS

Towards developing advanced driver specific active/passive safety systems, the ability to continuously evaluate driving performance will be necessary in next generation smart vehicles. One typical approach is to identify careless and risky driving events through analyzing abrupt variations in vehicle dynamics information. These variations are best captured when evaluated against similar driving patterns or maneuvers. This has been predominantly adopted in current day active safety systems [19, 20, 21]. These event detection systems provide an insight into the current driving conditions of the driver. In addition, every driver has his/her own unique style of driving. Along with weather and traffic, the driver's driving experience, vehicle handling ability, mental and physical state, all influence the way the maneuver is executed. Fig. 2 depicts such a system where the driver is identified based on his/her driving characteristics, maneuvers are recognized and variations in them are identified and the driving is classified. The driver identification sub-system reduces the variability for individual drivers, which can be achieved from face/speech recognition and other inputs. Next, the driving performance is evaluated by identifying maneuvers and detecting their variations against regular (normal execution) patterns. Finally, every driving instance (i.e. in terms of processing frames) is classified into neutral (normal driving) or distracted driving. This section is focused on the maneuver recognition, variation detection, and driving classification sub-systems for the distraction analysis.
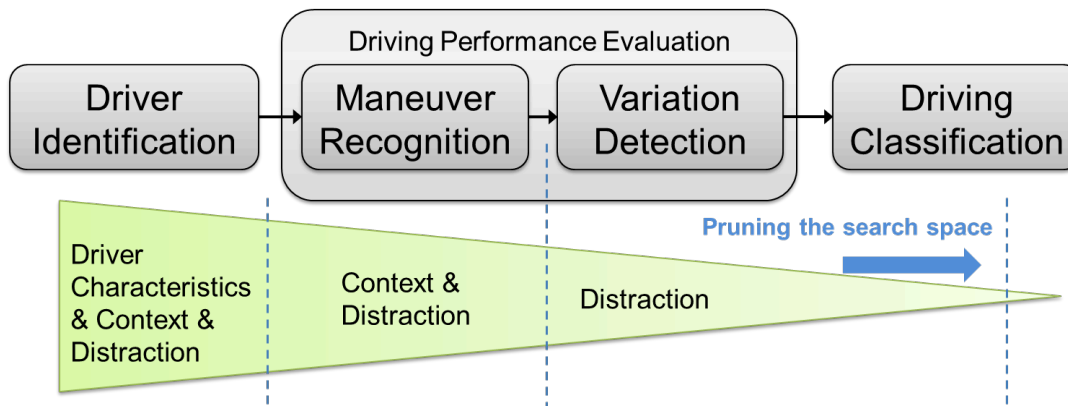
Figure 2: Driver dependent maneuver based distraction detection system

With the pending availability of massive free style naturalistic driving data corpus (i.e., SHRP2, NEDO – USA/Japan/Turkey [22, 23]), the development of automatic tools to organize, prune, and cluster driver centric based events for driver modeling is a growing research topic. Rather than using simulated or fixed test track data, it is important to analyze the on-road real-traffic naturalistic driving data for all possible driving variations in different maneuvers.

Human transcription of these massive corpora is not only a tedious task, but also subjective and hence prone to errors. These human transcription errors can potentially hinder the development of algorithms for advanced safety systems, and lead to performance degradations. Therefore, an automatic, effective, and computationally efficient tool is needed to help mitigate human transcription errors and make valuable data from large naturalistic driving corpora more accessible. In order to prevent these errors from propagating, an automatic maneuver activity (also boundary) detection system (or in short, a MAD tool) utilizing filter-bank analysis of vehicle dynamic signals is proposed. Using a minimal set of generic vehicle dynamic sensor information, such a MAD tool can match human transcription to an accuracy of up to 99% [24, 25]. Making this tool freely available will offer researchers opportunities to better explore naturalistic driving data.

3.1   *Maneuver Recognition*

Driving maneuvers, influenced by the driver's choice and traffic/road conditions, are important in understanding variations in driving performance and to help rebuild the intended route. Maneuvers are the basic units in building up a driving session. While processing of massive naturalistic driving data, it is essentially critical to analyze at a micro level. Understanding how these maneuvers are performed can provide information on how the driver controls the vehicle and how driving performance varies over time, and hence is essential in driver assistance and safety systems.

Similar to speech where phonemes form words, it has been established [26, 27] that the smallest meaningful units of a driving pattern are termed "drivemes"; drivemes form maneuvers, and maneuver sequences form a navigation route. This flow is depicted in Fig. 3. Therefore, tracking the variation on these "drivemes" can improve the efficiency of active safety systems in not only providing safety to the driver, but also in predicting drivers' actions.

Speech Recognition   Route Recognition

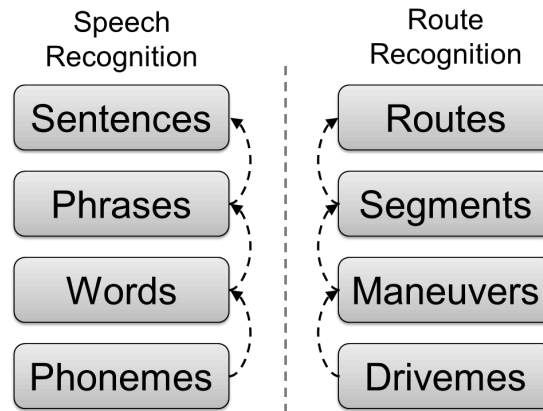| Sentences | Routes |
Phrases	Segments
Words	Maneuvers
Phonemes	Drivemes

Figure 3: Comparison of structural flow of building blocks between speech recognition and route recognition.

The definition of driving maneuvers may be considerably wide, depending on the underlying application [28]. Several existing studies have employed maneuver recognition for vehicle trajectory prediction [29], intersection assistance [30], and lane-change intent recognition on the highway [31]. Based on recent advancements, a study [32] that considered driving maneuvers primarily classified into 8 categories – straight, stop, left-turn, right-turn, left-lane-change, right-lane-change, left-road-curve, and right-road-curve showed promise.

The method of recognition in the literature employed various statistical modeling and machine learning classification algorithms, such as Bayesian models [33], Finite-state machines and Fuzzy logic [34], Hidden Markov Models [35], Decision Trees [36], etc. HMMs have proven to be beneficial in predicting driver actions within the first 2-second of an action sequence [37]. In our previous study, a similar HMM framework was employed in both a top-down as well as bottom-up approach to find the best integrated architecture for modeling driving behavior and recognizing maneuvers and routes [38]. Important features include steering-wheel-angle, speed, and brake signals from vehicle CAN-Bus data, or acceleration and gyroscope readings from smart portable device [39, 25]. In [40], recognition and prediction of lane-change maneuvers were proposed together, suggesting a double-layered HMM framework in the consideration of both maneuver execution and route information. Thus far, accuracy of maneuver recognition obtained range between 70%~90%, and offer opportunities for low cost, low level maneuver recognition for long-term modeling of driver modeling.

3.2   *Distraction Analysis*

Distraction in general affects the attention span of a person and within the vehicular space it manifests in the driver's vehicular controls. Traditionally, distraction has been assessed from the driver's perspective in terms of either stress, eye movements or cognitive workload [41]. Physiological measurements such as heart rate variability (HRV) and skin conductance (e.g., EEG, EMG) have proven to be useful in detecting the stress levels in drivers [42]. Studies have also considered body movement sensors to detect drivers' patterns in assessing driver distractions [43]. Though high accuracies have been achieved maybe from a research perspective, these vision and body worn sensors are intrusive and not suitable for naturalistic driving scenarios. Using such sensors can potentially serve as a baseline for ground truth while being compared with other non-intrusive sensors for performance.

Since driver actions and intentions manifest into vehicle movement, vehicle dynamic signals such as steering wheel, gas and brake pedal pressure and vehicle speed could potentially contain hidden/embedded information on the current situation of the driver. Using vehicle dynamic signals, driving is classified based on the maneuver execution characteristics of a particular driver. The classification could be a binary classification (neutral versus distracted) [46] or a trend in the variations (safe, moderate, or risky) [32].

The assessment of driving distraction underlies two hypotheses. First, the good, safe, or convenient driving behavior should be reflected with a stable, steady, or low-variance of vehicular dynamical performance. Second, an experienced driver should act in the "good driving" mode for the majority of the time, whereas "bad driving" may occur as a limited number of events [44]. Based on these hypotheses, the "good driving" events should be clustered in the vehicle dynamical feature space, whereas "bad driving" events will become more random anomalies/outliers.

Fig. 4 depicts a typical feature space for an imaginary maneuver type 'x'. The green squares, which are clustered together around the centroid of class 'x' represents the normal execution trend for this maneuver. The deviations from the normal execution pattern are reflected in the feature space of this maneuver as yellow or red squares. These "abnormal" instances of the maneuver are still recognized as type 'x' by the classifier but the intra class separation suggests that they can be marked as outliers. Euclidean distance, cosine distance and Mhalanobis distance has been used to detect outliers. Identifying such outliers help in the evaluation of driving pattern variations and driving performance [45]. Fig. 5 illustrates the gradient of event variations (classified as "safe", "moderate", and "risky") along with the driving route.
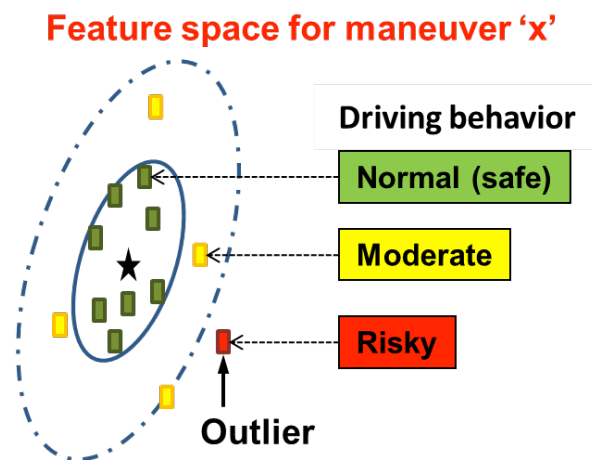

Figure 4: Example of feature space for maneuver 'x' with instance showing variations in driving performance and quantified as 'Normal', 'Moderate' and 'Risky' maneuver actions.
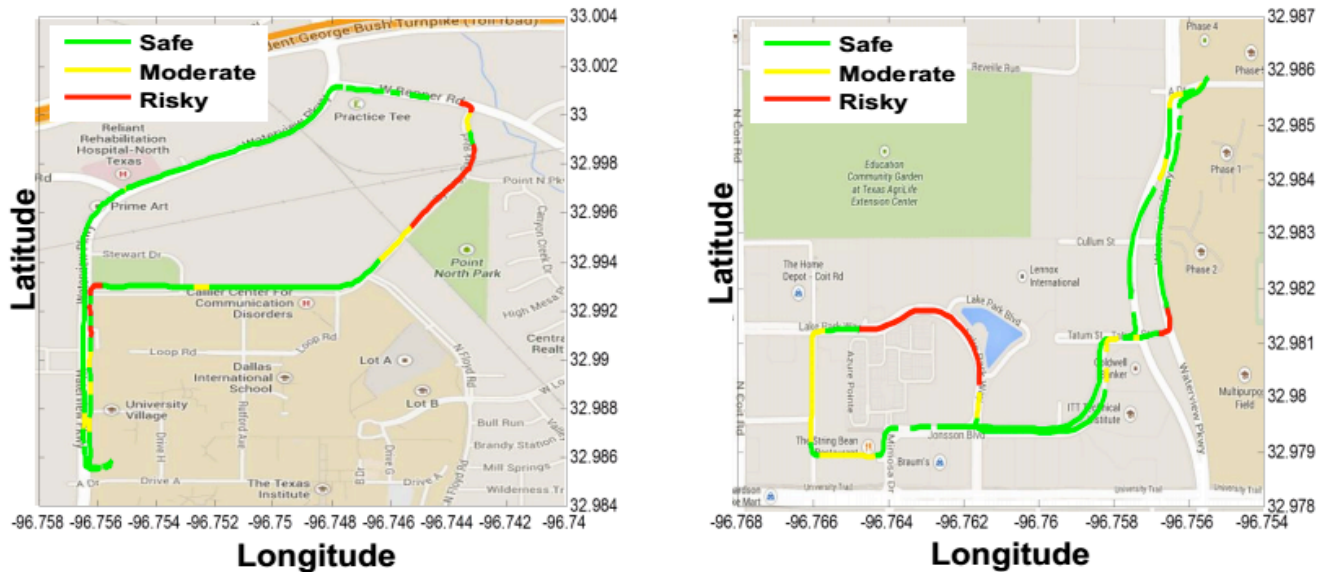
Figure 5: Maneuver variations along driving routes

Due to the highly dynamic nature of driving and the surrounding environment, drivers generally do not stay in one state for long and often toggle between models/states. A micro analysis on individual driving patterns is performed by segmenting the drive into small frames (few seconds or few meters travelled), which can be scaled to a macro level for preventing or correcting any unsafe activities. Such a micro analysis has provided an insight into how secondary tasks are executed by and influence drivers. Most secondary tasks can be grouped into 3 sequential events [46]. (i) Anticipation/Preparatory Phase, during the start of a task, when most drivers are distracted. This is justified as they divert more attention towards the task, assess the surroundings and get ready to perform the task. Then comes the (ii) Task Execution Phase where the drivers fall into a comfort zone of multi-tasking. Finally, (iii) Recovery or Post Completion Phase where drivers generally reassess their surroundings after secondary task completion. The duration of each of these phases are based on individual driver's comfort and confidence level [47], and the effect of multi-tasking is variable on different drivers. As the automotive industry further advances in developing ADAS, such driver centric adaptive systems will help in personalizing the vehicle by triggering ADAS only when drivers are impacted or when they show tendencies of such impact.

NHTSA released visual driver distraction guidelines [17] for in-vehicle electronic devices and considers visual, cognitive and manual as the main sources of distraction. It will not be long before the automotive industry and infotainment systems shift away from visual interaction with the driver and move towards audio/speech based interactions with the driver. Therefore, it is of great interest to understand the actual influence of in-vehicle speech on the driver. There is some preliminary work done in this area to understand the influence of in-vehicular speech and audio in driving [48]. It is shown that while some in-vehicle conversations might aide driving, there are categories such as involved, competitive and argumentative speech that can adversely influence the driver and cause driver distraction.

4   TRACKING GLANCE BEHAVIOR AND VISUAL ATTENTION

An important aspect in monitoring driver distraction is to evaluate the visual attention of the driver. There are three main areas that can benefit from tracking the drivers' visual attention: assessing primary driving task, detecting secondary tasks, and supporting advance user-computer interfaces.

4.1   Role of Visual Attention

Understanding where the visual focus is becomes a key step to determine driver performance during primary driving task [49~51]. A driver has to scan the route environment before conducting a driving maneuver. This action includes checking the mirrors, looking at front vehicles, and identifying pedestrian actions. In fact, primary driving tasks such as visual scanning, turning and switching lanes require mirror-checking actions [52~54]. Failing to accomplish these tasks decreases the drivers' situational awareness, increasing the chances of accidents [55, 56]. An increase in visual demand due to secondary tasks affects the control of the vehicle, detection of critical traffic events, and the detection of hazard events [57]. As a result, studies have used features describing eye-off-the-road, head pose, gaze range and eyelid movements to detect distractions [58~65]. Objective measures capturing duration and frequency of glance behaviors can provide important information to provide warnings to distracted drivers.

Visual attention signals temporal deviations from the primary driving task to complete secondary tasks such as turning the radio, operating a cellphone, or looking at other passengers. All these secondary tasks induce visual, cognitive, auditory, and manual distractions. A perceptual evaluation has been conducted to assess the perceived level of cognitive and visual distractions of 10s videos of drivers while engaged in different secondary tasks [65, 66], in which the advantages and limitation of using perceptual evaluations to assess driver distractions is discussed. Fig. 6 shows that many common secondary tasks induce high level of visual distractions. For example, operating a cellphone, the radio or a navigation system increases the perceived level of visual distractions [67]. Lack of glances can also signal cognitive distractions where the driver is looking but not seeing (daydreaming, mind wandering) [68, 69]. These types of distractions are very difficult to detect with noninvasive sensors [70]. Tracking glance behaviors provide an important tool to address this problem. For all these reasons, a robust ADAS should be able to detect mirror-checking actions and glance behaviors to prevent hazard situations [71].
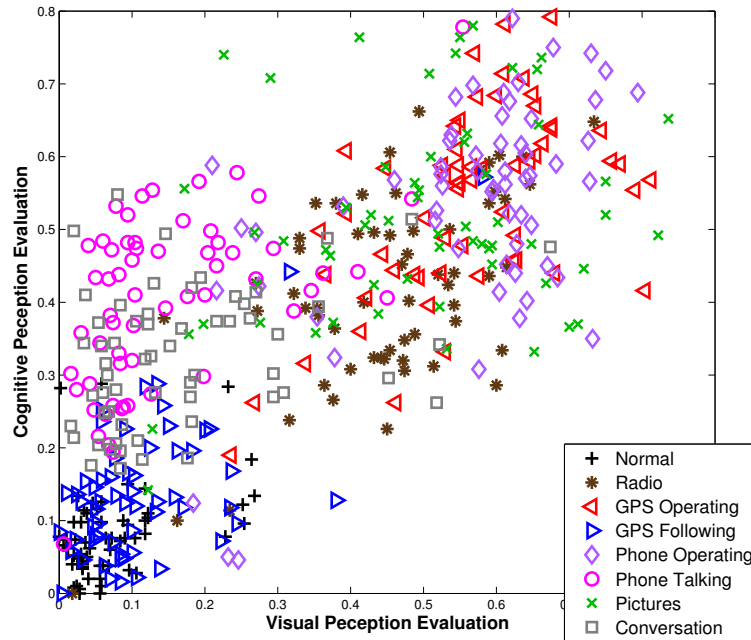
Figure 6: Visual-cognitive space proposed to study driver distraction. Perceptual evaluations are used to determine perceived level of distractions. Different secondary tasks affect driver distraction differently.

The automobile industry is developing new advanced interfaces that do not induce manual or visual distractions. These interfaces are generally implemented using automatic speech recognition (ASR) systems. ADASs need to provide essential information to the driver in an effective manner. With more information available to the driver, it is also important that the information is presented without causing significant distractions. By tracking the visual attention of the driver and environment, ADAS can clarify ambiguities providing situated dialog system (e.g., commands such as "what is the address of this building?" while glancing toward a specific building). In an example of such a system [72], the visual saliency of the scene and crowdsourced statistics on how people describe objects were used as prior information to improve the identification of point-of-interests (POI). While the visual saliency of the scene did not depend on driver glance behaviors, we expect improved performance by modeling the visual attention of the drivers [73,78].

4.2   Tracking Visual Attention

Tracking eye movement can be an accurate measurement to identify the exact location of the gaze of the driver. However, robustly measuring gaze in a driving environment is challenging due to changes in illuminations in the vehicle, and changes in head poses from the drivers. As a result, most of the studies have approximated gaze with head poses. Zhang et al., [74] argued that, even though eye gaze is a better indicator, head pose alone can provide good cues about driver intentions. However, there are difference between head pose and the actual gaze that needs to be considered [75~78]. The driver moves his/her head and eyes to glance at a target object, where the eye-head relationship depends on factors such as the underlying driving task, the type of road, and the driver.

Studies have investigated the relation between head motion and gaze on naturalistic recordings [78]. We placed multiples markers on the windshield, side windows, speedometer panel, radio, and gear. The recordings

protocol is repeated while driving and when the car was parked. We proposed regression models where the dependent variables were the position and rotation of the head, and the independent variables were the 3D position of the POI. While driving, the R^2 of the model was about 0.73 for the horizontal direction, but lower than 0.20 for other directions. Motivated by these results, the analysis is extended to incorporate a probabilistic model relying on Gaussian Process Regression (GPR) [79]. Instead of deriving the exact location of the POI, the framework creates a salient visual map describing the driver visual attention, which is mapped into the route scene (see Figure 7). The 95% confidence region of the models included about 89% of the POI. This approach provides a suitable tool for situated dialog systems, and safety systems that are aware of the driver glance behavior.

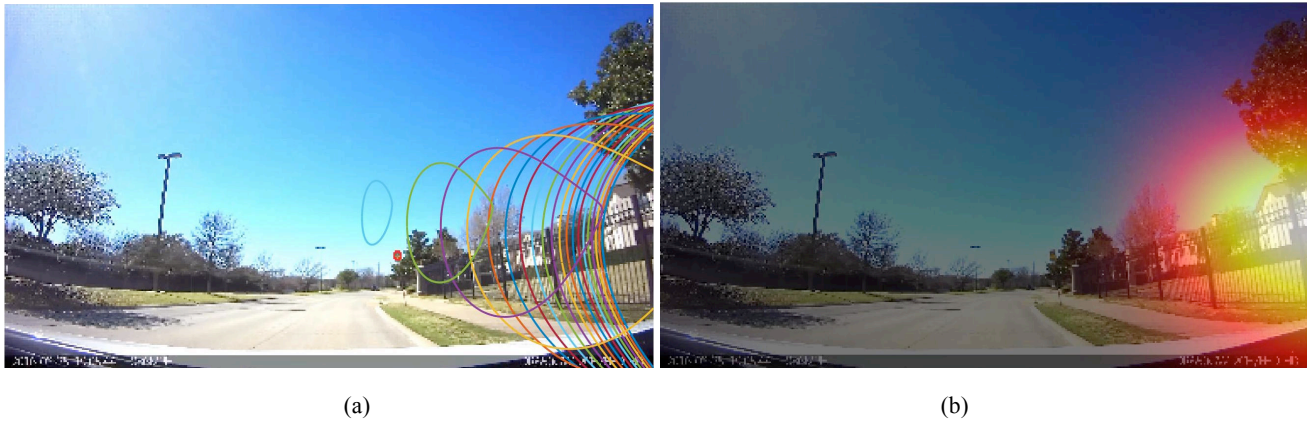(a)   (b)

Figure 7: Visual saliency map created with the probabilistic model. (a) estimation of confidence regions for different distances from the car (b) aggregation of the results projected on the road camera. The saliency map characterizes driver visual attention.

An alternative approach of monitoring visual attention is to directly recognize primary or secondary driving tasks that require visual demand. An example of primary driving task is the detection of mirror-checking actions. We presented an accurate *random under-sampling boost* (RUSBoost) classifier to recognize mirror-checking actions [71]. The classifier was trained with multimodal features automatically extracted from the driver and road cameras, and the CAN-Bus signal using naturalistic recording on the UTDrive platform. The task was to recognize each time the driver looked at a given mirror.

Fig. 8-a shows an example of a participant looking at the rear mirror. The F-score of the classifier was 91.4%, which is very high given that mirror-checking actions are infrequent events making this classification problem highly unbalanced. Fig. 8-b shows the performance for different routes, for normal condition (black bars - driver is not engaged in secondary tasks) and task conditions (gray bars - driver is engaged in secondary tasks). The classifier showed consistent performance across normal and task conditions. An example of secondary task is the detection of activities not related to the driving task requiring visual activities. We trained binary classifiers using *support vector machine* (SVM), which detect particular secondary activities [60]. For task such as looking at pictures (which simulate the task of looking at billboards, sign boards and shops), and operating a radio and a GPS, the accuracy was about 80%. The perceptual evaluation showed that these tasks induce high visual demand.
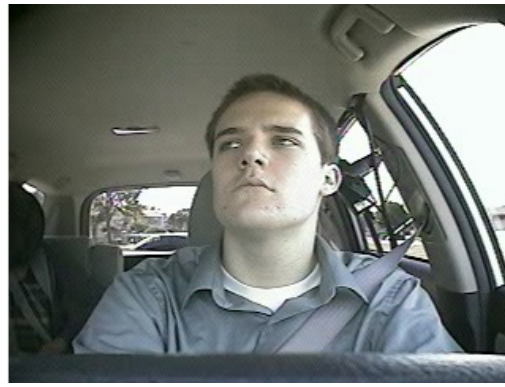
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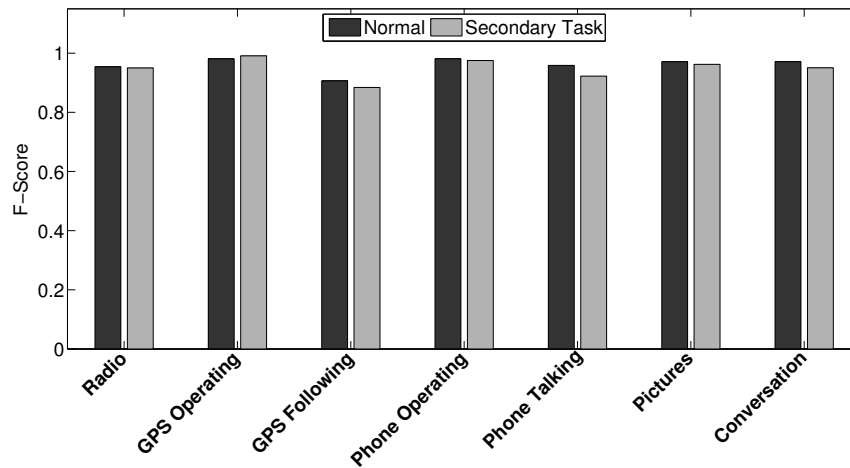
(b)

Figure 8: Mirror-checking detection using multimodal features. (a) a participant looking at the rear mirror, (b) the F-score of the classifier for normal and task conditions.

5   PORTABLE PLATFORM ADVANCEMENTS

With the rapid growth of smartphone capabilities including entertainment and management of daily activities, individuals are increasingly employing smartphone use during driving. However, operating a vehicle is a complicated and skillful task requiring multi-modal (especially visual) attention and focus. While drivers are managing multi-tasks comfortably, using a smartphone may become a distraction and contribute to increased risk. Alternatively, the proper use of smart devices could be a source of reduced driving distraction while executing secondary tasks. Studies have also shown that drivers can achieve better and safer driving performance while using speech interactive systems to operate in-vehicle systems compared to hand operated interfaces [80].

A more advancing reason for introducing the smartphone is its potential ability to be integrated with intelligent telematics services. Smartphone-based on-board sensing in the vehicle is able to capture various sources of information, including traffic (other vehicle and pedestrian movements), vehicle (diagnostics), environment

(road and weather), and driver behavior information [81]. It would be beneficial to connect this platform with ITS or Vehicle-to-Vehicle or Vehicle-to-Infrastructure (V2V/V2I) communication, share the information, and realize a wider Internet-of-Vehicles. However, challenges of smartphone platform use in the vehicle come from the deployment difficulty, measurement accuracy, as well as system reliability.

In this section, we will first discuss the deployment of smartphone as an in-vehicle data collection platform, utilizing its hardware resources. Additionally, we will explore the implementation for the voice-based human-machine-interface, as well as its capability in applications for vehicle/driver telematics.

5.1   In-vehicle Data Collection Platform – Mobile-UTDrive App

Smartphones contain a variety of useful sensors including cameras, microphones, Inertial Measurement Units (IMU) and GPS. These multi-channel signals make the smartphone a potentially leveraged platform for in-vehicle data sensing and monitoring, and can be employed for the driving distraction analysis. The use of smart portable devices in vehicles creates the possibility to record useful data and helps develop a better understanding of driving behavior. This option allows a wider range of naturalistic driving study opportunities for drivers operating their own vehicles [82~84].

In the past few years the UTDrive mobile App (i.e. Mobile-UTDrive) has been developed with the goal of improving driver/passenger safety, while simultaneously maintaining the ability to establish monitoring techniques that can be used on mobile devices on various vehicles [85]. Mobile-UTDrive has been primarily used and developed as a multi-modal data acquisition platform, which is to collect driver, vehicle, and environment information that describing the comprehensive driving scenario. The modalities captured by Mobile-UTDrive are audio, video, GPS, and IMU sensor signals. The app runs on any android-based smart portable device and uses its front and rear cameras to record naturalistic driving video as well as in-vehicle audio. The IMU and GPS within the device provide accurate estimates of vehicle dynamics. More recently, Mobile-UTDrive has been further developed to take advantage of capabilities such as speech recognition and on-screen map navigation. Fig. 9 displays the screenshot of Mobile-URDrive App running on a tablet. Using this approach has resulted in studies to detect maneuvers, and design driving safety systems that combine in-vehicle speech and video analysis and driving performance evaluation [86, 87]. Freely distributing this platform will offer researcher the opportunity to customize their data collection scenarios while maintaining current goals for naturalistic driving data advancements.
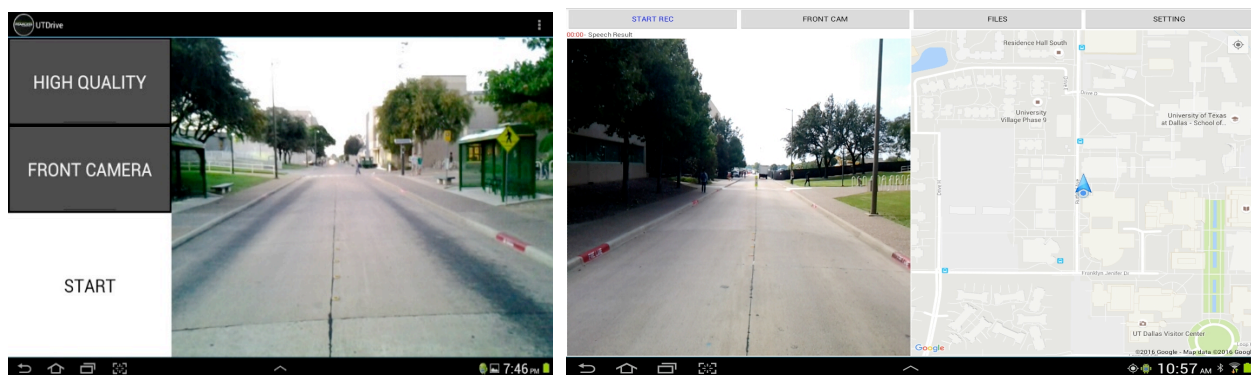

Figure 9: Mobile-UTDrive App display: (i) original (left) and (ii) updated version (right)

In previous studies, it has been shown how vehicle dynamic signals can potentially replace the information extracted from a CAN-bus and thereby extend the use of maneuver recognition and monitoring algorithms to any vehicle that uses the App [32, 45]. However, the orientation and relative movement of the smartphone inside the vehicle yields the main challenge for platform deployment. A recent study [88] proposed a solution of converting the smartphone-referenced IMU readings into vehicle-referenced accelerations, which allows free-positioned smartphone for the in-vehicle dynamics sensing. In this proposed framework, the raw smartphone IMU readings are first processed through a geometry coordinate transformation to rotate/re-orientate the smartphone-referenced accelerations into a vehicle-referenced coordinate system. Next, a regression model is established to map the relationship between IMU and GPS data, and therefore provide an adaptively filtering process to decouple the smartphone's relative movement in the vehicle. This serves as a pre-process module and therefore provides the basis for further applications using the smartphone data (see Fig. 10).
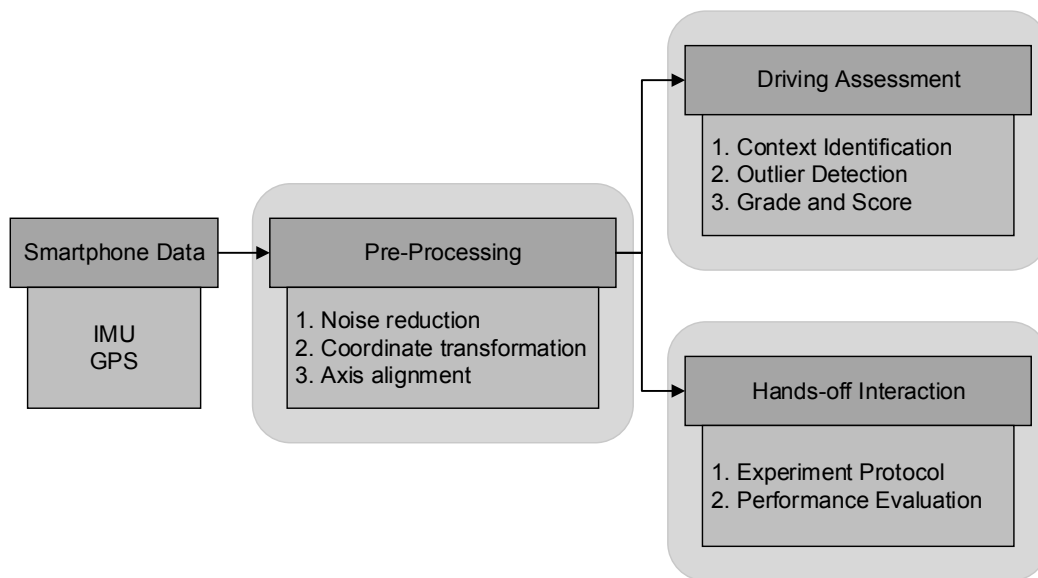

Figure 10: Smartphone data processing modules

5.2   *Voice-based Human Machine Interaction*

The smartphone in the vehicle provides an easy access to the speech recording, processing, and potential integration with the infotainment system, which becomes a good platform for the development of voice-based human machine interface. In terms of tasks such as setting map navigation, changing the radio station, adjusting volume, adjusting AC, and control of windows, drivers are not necessarily required to perform these with hands-on operation but employ voice commands instead. The typical manual-entry or tactile-based engagement primarily utilizes various combinations of keypads, keyboards, point and click techniques, touch screen displays, or other interface mechanisms. These traditional eyes-off-road interfaces tend to be cumbersome in environments where the speed of interaction and dangers of distraction pose significant issues, and therefore fall short in providing simple and intuitive operations. In contrast, voice-based interaction would keep the drivers' eyes focused on the road while avoiding hands off-the-wheel. Results have shown that hands-on operation could potentially be a greater cause of major irregularities in driving performance, despite the latency and recognition error imposed by the speech recognition system [87, 45]. The development of speech recognition compatibility and natural language understanding for dialog interaction in the car offers avenues

for lowering driver distraction. Therefore, natural voice-based engagements between driver and vehicle offer the potential to meet an ever-growing demand for creating a comfortable, safe, and convenient driving experience.

Among the voice-based human-vehicle interfaces, the navigation dialogue system is the one with the highest demand in recent years. Navigation dialogues are possibly proceeded while a user may be driving, on-the-go, or in other environments where having a hands-free interface provides critical advantages. A desired intelligent navigation system is far beyond searching locations on the map, it would have the capability acting as an assistant, "talk" with human in a natural way, and "guide" and "drive for" human. Therefore, the ability of human's natural spoken language understanding is needed. For example, when a driver is trying to find a destination, he/she may either speak out a point-of-interest (POI), specify the exact address, or spell the name and number of a street. The navigation system should automatically understand it without having to ask the driver to choose the "style" of their spoken languages. Furthermore, in the next generation autonomous driving vehicles, it is expected that the vehicle will automatically ride for human. Passengers may inquire about the trip or change the previously selected route through the dialogue system, and the vehicle should be able to understand how it is associated with navigation tasks and provide necessary responses.

Recent studies [89, 90] consider the Natural Language Processing (NLP) for the navigation-oriented human-vehicle dialog. The NLP framework is based on a Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) architecture, and contains the sentence-level sentiment analysis and word/phrase-level context extraction. As shown in Fig. 11, the sentiment analysis is to identify whether a sentence is navigation or non-navigation related. For the navigation-related sentence, the next stage is to extract useful context by recognizing the word/phrase labels. The extracted information will be ready to submit for response or path-planning. The NLP accuracies were experimented within 70%~98%, depending on its prior stage – speech recognition results.
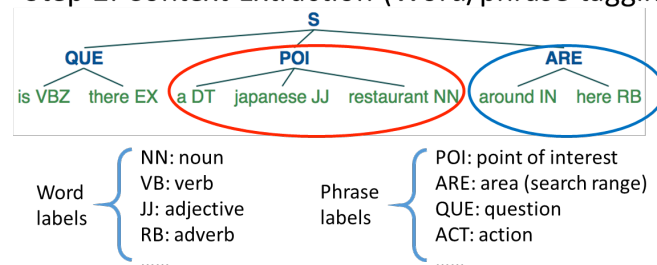

Figure 11: An example of natural language processing tasks. For the sentiment analysis of two sentences, a) is non-navigation and b) is navigation-related. b) is further processed with context extraction, and useful information (point of interest, search area) is labeled.

6   DISCUSSION & CONCLUSIONS

Vehicle technologies have advanced significantly in terms of improved transportation, comfort and safety, and will continue to evolve as we move forward into the next generation of transportation systems and infrastructure. From this article, as well as the broad coverage from recent papers in the special issue (IEEE Signal Processing Mag. Nov. 2016), it is clear that new technologies are migrating into novel in-vehicle systems for route navigation, information access, infotainment, and connected vehicle advancements for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) connectivity/communications. Vehicle driving autonomy is also evolving – and so further research advancements are needed to better understand the interplay between driver, vehicle, and route/environment. With the motivation of contributing to improved intelligent driver-vehicle systems that incorporate human-specific characteristics, the CRSS-UTDrive Lab has focused their research on naturalistic driving studies, with the interest of understanding driver behavior and distraction from multi-channel sensor data. Any secondary driver task activity in the vehicle can be a source of driving distraction, and therefore impact driving performance in an unusual way. Regarding this, one typical approach is to first extract the driving context in terms of micro-level components (e.g., maneuvers), and then evaluate risky events/variations against similar driving patterns in the vehicle dynamics domain. An alternative approach is to directly monitor drivers' physical or glance behavior, and assess their cognitive and visual attention. Previous studies have shown precise results in the detection of driving distraction, driving performance analysis, and visual attention tracking. In addition, to benefit the fast-growing smartphone applications and integrate telematics services, more recent activities have resulted in a mobile platform, which contributes to in-vehicle naturalistic driving studies and voice-based human-machine interfaces. These studies, if combined together, would be able to provide a comprehensive understanding of the driver's state and driving performance, establish a comfortable driving experience with human-centric assistant in the vehicle, as well as contribute the intelligent transportation information sharing via V2V/V2I connectivity. This study has explored (i) driver behavior and distraction, (ii) maneuver recognition and distraction analysis, (iii) glance behavior and visual tracking, and (iv) mobile platform advancements for in-vehicle data collection and human-machine interface. Finally, while there is great interest in migrating to fully automated/self-driving vehicles, next generation vehicles will need to be more active in assessing driver awareness, vehicle capabilities, traffic/environmental settings, and how these come together to determine a collaborative safe and effective driver-vehicle engagement for vehicle operation. Greater interdisciplinary research that addresses multi-functional vehicles to support smooth transitions from complete human control towards semi-supervised/assisted, to fully automated scenarios are needed. In the end, while signal processing technical advancements can enhance vehicles, comfort, enjoyment and capabilities of drivers, to be successful these efforts must first do no harm and ensure improved safety.

7   BIOGRAPHIES

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