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Selection of Measurement Method for Detection of Driver Visual Cognitive Distraction: A Review

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ABSTRACT Driving distraction is a topic of great interest in the transport safety-research community, because it is now a primary cause of road accidents. A recent report has revealed that distraction is more alarming than previously thought, and a suitable measurement to effectively detect distraction is required. Most agree that driving distraction actually comprises the simultaneous interaction of two or more types of distraction. The purpose of this paper is, therefore, to determine the promising method for measuring visual cognitive distraction. We discuss the five common measurement methods for visual and cognitive driving distraction, which include driving performance, driver physical measures, driver biological measures, subjective reports, and hybrid measures. Hybrid measurement of driver's physical measures (e.g., eye movement) and driver's biological measures (e.g., electroencephalogram) is better than other methods at detecting types of visual cognitive distraction. This new perspective on measurement methods will help the field of transport safety to determine the best means of detecting and measuring the effect of visual cognitive distraction.

INDEX TERMS Driving distraction, cognition, visual, detection.

I. INTRODUCTION

Along with alcohol and speeding, in past decades, driving distraction began to emerge as a leading factor in fatal and serious injury crashes [1]. About 20% to 80% of crashes and near crashes are caused by driver distraction, as determined by the National Highway Traffic Safety Administration (NHTSA) of the USA [2].

A study conducted by the AAA Foundation for Traffic Safety revealed that young drivers were distracted in 58% of the analyzed crashes [3], while the NHTSA reported only 13% to 14% of all drivers were distracted in 2014 [4], 2013 [5], and 2012 [6]. The disparity between these two reports is the method of analysis. The data analysis used by the AAA Foundation for Traffic Safety was based on six-second video clips that were captured just before the crashes occurred. In contrast, the NHTSA focused on crash data that were subjectively reported. The large percentage differences in these reports may indicate that the number of accidents resulting from distraction is probably greater than what we previously thought. However, lack of common measurements makes interpretations and conclusions difficult. Thus, an objective and reliable measurement of distraction is required before proposing any appropriate mitigation action.

Among the 40% of intersection-related crashes in the USA that occurred in 2008, recognition error (56.7%), and detection error (29.2%) were reported as the most critical factors that contributed to the crashes [7]. These statistics indicate that human factors such as driver awareness are the main cause for these kinds of accidents. A more recent study of young drivers revealed that passengers are the main reason for driver distraction (40%), followed by cell phones (12%), and unknown people/objects outside the vehicle [3]. Based on this evidence, driver experience level might influence the ability to stay aware.

In addition to these issues related to distraction—which are not yet fully understood—the emergence of autonomous car technology is another factor that will affect driver awareness. According to NHTSA's Federal Automated Vehicle

Policy [8], there are six levels of vehicle automation that have been defined to facilitate discussions between different agencies and stakeholders. The levels range from level 0 (no automation) to 5 (fully automated). Levels 2 to 4 allow drivers to give driving authority to the automated system, and consequently permit drivers to reduce how much attention they give to driving and the road. Thus, in automated driving, the driver is allowed to be distracted as they are encouraged to disengage from driving [9]. Although the guidelines clearly state that human drivers must continue to monitor the driving environment at these levels, questions persist. In particular, how much a driver can be distracted or disengaged and still maintain a safe driving environment is remains unclear. Further, we do not know which are the reliable and suitable measurements that can help in investigating and eventually proposing mitigation actions for safety reasons.

In this paper, we hope to summarize the common measurements for detecting distraction, specifically visual cognitive distraction. The organization of the paper is as follows: Part II: Visual and Cognitive Driving Distraction and Part III: Distraction Measurement Methods.

Part II summarizes the relationship between attention and situational awareness to visual cognitive distraction. Part III begins with introducing the common measurement methods and then summarizes the advantages and limitations of adopting these measurements for detecting visual cognitive distraction.

II. VISUAL AND COGNITIVE DRIVING DISTRACTION

A. ATTENTION

Driving distraction is defined as a shift in attention away from safe driving towards a competing task [10]. The source of distraction/competing task could originate from the external environment [10] as a salient stimulus that captures attention in a bottom-up fashion [11]. The distraction could also originate internally, a phenomenon known as cognitive distraction [10], which utilizes internal attention [12]. Attention is the core property of all perceptual and cognitive operations, and its basic characteristic is its limited capacity [11], [12]. Because of this characteristic, people need to select the focus of attention, either towards driving or towards the distraction.

The first stage of attentional mechanisms as described by Chun *et al.* [12] is selection from multiple sources, either internal or external, which are driven by bottom-up or top-down forces, respectively. Once a focus has been set, the captured information is modulated in the second stage. During this stage, the information is interpreted at either fast or slow processing speeds, and a decision is made as to whether it will be remembered, forgotten, or executed. The third stage of the attentional mechanism is the state of vigilance, also known as sustained attention, which represents a consistent focus on the subject of interest.

The attentional bottleneck caused by the selection stage can be understood well by observing visual attention [11]. Therefore, when we compare this attentional mechanism [8] with the perceptual process described by Goldstein [13], we can see that they fit well together (Fig. 1, red circles 1 and 2). This represents the selection stage of the attentional mechanism. The light reflected from the stimulus reaches photoreceptors in the eye and is transduced into an electrical signal that then travels to the occipital region of the brain through the optic tract. Different information embedded in the stimulus then travels to the dorsal (parietal region) and ventral (temporal region) streams where it is perceived and recognized [14]. The brain then decides on the course of action in the frontal region. The processes denoted by red circle 5 in Figure 1, represent the modulation stage within the attentional process. As the perceptual process is repeated, the state of vigilance is strengthened.

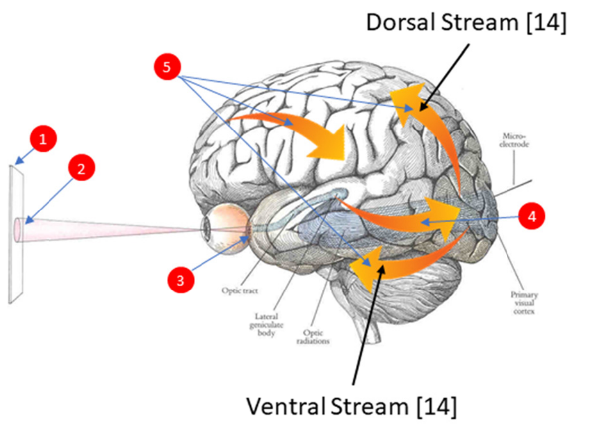

FIGURE 1. The visual pathways.

In spite of the attentional bottleneck, driving distraction is also influenced by strategic workload management that heavily depends on the driver managing interruptions that direct attention toward distractions. This is extensively discussed by Lee [9] as the process of engaging and disengaging during driving. A failure in interruption management occurs when drivers disengage from driving and spend more time attending to the distractor [15], a phenomenon that is a type of task preservation. Factors that influence task preservation are proximity, goal emergence, and goal valence, which are similar in concept to goal activation [16].

These attentional traps are mostly driven by volitional top down attentional control because drivers are willingly shifting attention to the distractor [17]. This is a similar concept to internal attention as described by Chun *et al.* [12]. Therefore, we can conclude that even though we shift our attention based on the origins of the distractor, consistent disengagement from driving to attend to distractions is mostly driven by internal attention. Internal attention involves cognitive control processes and operates over representations in working memory, long-term memory, task rules, decisions, and responses [12]. Thus, detecting a single type of distraction does not trigger the complete distraction process. However, engaging in and disengaging from the driving distraction during driving does involve cognitive control.

The current opinion in neurobiology [11] is that focusing on attention arises from the interaction between widespread cortical and subcortical networks that may be regulated via their rhythmic synchronization. Neural signals reflecting the bottom-up control of attention are thought to originate in the parietal cortex. In contrast, network interaction for top-down control of attention seems to originate from the frontal cortex [18].

TABLE 1. Summary of brain activity during perceptual switching.

References	Remarks
[24] [23] [22] [21]	Some oscillatory EEG activity, especially delta band (around 4 Hz) activity, has been shown to correlate with perceptual switching.
[20]	The fronto-parietal delta-band oscillatory EEG coherence was suggested as an important component for general attention-demanding cognition.
[19]	3–4 Hz spectral EEG power was modulated at fronto-central, parietal, and centro-parietal electrode sites during perceptual switching. (Dorsal Attention Network – DAN)

Given that the definition of distraction relates to the shifting of attention away from safe driving and towards some competing task [10], drivers may be performing perceptual switching (the selection stage of the attentional mechanism) when distracted. Table 1 summarizes the findings related to brain activity during perceptual switching.

It has been observed that compared with other frequency-band oscillations, perceptual switching involves synchronization of low frequency brain activity [19]–[24] that occur in the frontal, central, and parietal regions of the brain. We speculate that low frequency oscillations will be synchronized during distracted driving as well. This is because most sources of distraction comprise two or more type of distraction [25].

Studies of driving distraction typically assess the effect of distraction that results from a single type of distraction. As classified by the NHTSA, these include visual, cognitive, auditory, and physical/biomechanical distractions [26]. Visual distraction is defined as taking the eyes off the road, cognitive distraction as taking one's mind off the task of driving [27], auditory distraction as taking one's ears off of auditory driving cues, and physical distraction as taking one's hands off the wheel [1].

Several other common secondary tasks that drivers tend to perform and are also considered to be sources of distraction. A review by Young and colleagues [25] has classified sources of distraction into three categories: (1) technology-based, (2) non-technology based, and (3) external-to-vehicle. Technology based distraction includes the usage of in-vehicle communication systems such as talking on mobile phones (hands free or not), texting, emailing, or searching for an address using the GPS. Using mobile phones requires attention to visual, cognitive, and physical functional processes. Because of its complexity and importance, many researchers are focusing on this issue from different perspectives [28]. Non-technology based distractions include, but are not limited to, talking to passengers, eating, drinking, smoking, or trying to become unlost, which actually causes more than one type of distraction. For instance, trying to determine where one is involves looking for important cues (e.g., street signs, landmarks, etc.), and thus drivers might take their eyes off the road to examine the surrounding area (visual distraction). At the same time, cognitive skills are required to compare this to any remembered information related to the desired location and then plan the next action (cognitive distraction). All this increases the load on the main cognitive task: driving.

External-to-vehicle distraction involves visual and cognitive capacity during driving. Looking at events, people, billboards, or car crashes while driving are classified in this category. Attending to salient stimuli such as pedestrians crossing the road is important; however, even this could be a distraction if the driver is not aware that the car in front of him has put on an emergency brake. Another example that fall into this category comes from a study on distraction caused by commercial electronic variable message signs (CEVMS). The study concludes that these signs attract more and longer glances than regular traffic signs [29]. This attracts visual attention and may use cognitive resources in order to understand the message being displayed.

Thus, the sources of driving distraction are less likely to be best represented by a single distraction type. Rather, a combination of two or more distraction types or phenomena can capture a more realistic situation. Most technology-based tasks commonly require both visual and cognitive effort [30]. This is also the case for the other categories of distraction source; non-technological based and external from vehicle.

B. SITUATIONAL AWARENESS

We have described the cause of driving distraction as being due to the limited capacity of attention. Therefore, a driver needs to engage in frequent perceptual switching when distracted. However, this limitation directly affects the driver's situational awareness. Perceptual switching (i.e., the selection stage of the attentional mechanism) makes it possible for drivers to perceive their surround, even though attention itself allows them to focus on something else at the same time [31]. Because environmental stimuli and task state change constantly, drivers are required to continuously make decisions. Considering this fact, situational awareness can be severely affected when distraction by a competing task leads to the failure to notice important stimuli.

Endsley [32] introduced a model of situational awareness in a dynamic system that can ideally describe the effect of failing to notice an important stimulus because of the limited capacity for attention. According the model, there are three levels of situational awareness. The first is "the perception of the elements in the environment within a volume of time and space," the second is "the comprehension of their meaning," and the third is "the projection of their status in future." Decisions can be made and actions can be performed once each of these levels has been achieved. However, failure to notice an important stimulus at the first level will certainly affect correct comprehension of the current situation and projection into the future, leading to errors in decision-making, and eventually causing an accident.

Although driving can be considered part of procedural memory to an experienced driver, being aware of the current situation is always necessary so that one can adapt to a changing environment. Procedural memory is a type of memory that becomes more efficient as practice of skills continues and actions can be performed automatically with little conscious thought or recall [33]. Studies [34], [35] have shown that experienced drivers observe hazards and demonstrate overt recognition of hazards more frequently than teen drivers. Additionally, a large portion of teen drivers fail to disengage from competing tasks in the presence of hazards. However, this efficiency does not apply to all ages of experienced drivers. Age-related declines in cognition may have detrimental effects on the ability of older adults to complete everyday tasks. Consequently, their situational awareness is lower when compared with that of younger and middle-aged adults [36], [37]. Therefore, we can infer that situational awareness and driving experience are the primary two elements that influence distraction levels when driving.

III. DISTRACTION MEASUREMENT METHODS

There is a limitation to how well we can perform multiple tasks simultaneously [38], without performance on all tasks being degraded [39]–[45]. Therefore, attending to a competing task while driving is a distraction that degrades one's driving performance and affects one's safe driving behavior. This section discusses five methods for measuring visual and cognitive driving distraction, and how they can contribute towards detecting distractions. The five common measurements of driving distraction are: (a) driving performance measures, (b) physical measures of the driver, (c) biological measures of the driver, (d) subjective reports, and (d) hybrid measures [46].

A. MEASURES OF DRIVING PERFORMANCE

Measures of driving performance quantitatively measure driving behavior, and are mostly used to investigate the effects of distraction. Common measures of driving performance for this purpose are speed, lateral control, and reaction time.

1) VISUAL DISTRACTION

a: SPEED

Drivers generally slow down when distracted by a visual stimulus [30], [47], [48]. This can be explained as a compensatory mechanism for the perceived risk, which can be lessened through reduced speed. However, findings by Young *et al.* [49] contradict those from previous research. In her study, increased speed was not only evident in the higher mean speed, but also in the significant number of speed violations made when distracted. She speculated that the inconsistencies were because the noise in the vehicle was very low and drivers tended to monitor the speedometer less than usual.

b: LATERAL CONTROL

Generally, visual distraction impairs lateral control because the driver needs to compensate for errors made when taking the eyes off the road, which leads to larger deviations in lane positioning. This has been proven in several studies that reported increased lane-position variability [48], [50]. Steering control is also reported to be less smooth than in normal driving [50]. However, Young *et al.* [49] has shown otherwise. In her study, the standard deviation of lateral control did not significantly differ between normal and distracted driving. The central placement of the distracted stimuli in the driver's field of view may have contributed to this contradicting result.

c: REACTION TIME

Reaction time is evaluated by several measures: Brake Reaction Time, Peripheral Detection Time (PDT), and Detection Response Time (DRT). The purpose of this method of assessment is to evaluate the mental load of the driver. There are no current reports that relate visual distraction with reaction time.

2) COGNITIVE DISTRACTION

a: SPEED

Cognitive distraction causes mixed responses on vehicular speed. Studies by Engström *et al.* [30] and Caird *et al.* [51] reported that cognitive distraction did not have any effect on speed. However, Rakauskas *et al.* [52] showed a decreased mean speed because of high-level workloads. In contrast, Törnros and Bolling [48] and Recarte and Nunes [53] found that cognitive distraction leads to increased speed because attention is required to maintain a constant speed. They argued that distraction prevents drivers from regularly checking the speedometer, which raises the tendency to increase or decreased speed. Evidently, these responses depends on one's driving habit [54].

b: LATERAL CONTROL

Studies have shown that cognitive distraction has a very small effect and no significant influence on lane deviation [48], [50], [52].

c: REACTION TIME

Studies on reaction time during cognitive distraction unanimously report that reaction time increases during distraction [52], [55]–[57]. Some studies have also shown that miss rates increase [52], [56].

Table 2 summarizes the effects of visual and cognitive distraction as described above. The advantages of using driving-performance measures to compare the effects of visual and cognitive distraction is that the two distraction types induce different responses except for speed, which shows mixed responses. However, inferential detection is not an effective

TABLE 2. Summary of the effects that visual and cognitive distraction have on driving performance.

Type of Distraction / Performance Measure	Visual Distraction	Cognitive Distraction	Remarks
Speed	• Reduce speed [30, 47, 48]. • Increased speed [49].	• Reduce speed [52]. • No effect on speed [30, 51]. • Increased speed [48, 53].	Mixed responses
Lateral Control	• Increased lane position variability [48, 50]. • *No significant differences [49].	• Very small deviation to no significant influence of lane deviation [48, 50, 52].	Distinctive response between distraction type (excluding the biased response*)
Reaction Time	There is no current report that relate visual distraction with reaction time.	• Increased during distraction [52, 55-57]. • Increased miss rate [52, 56]	

technique for detecting distraction because other factors such as bad driving habits could affect the responses, and lead to false-positive detection [54]. For instance, although visual and cognitive distraction affect lateral control differently, a small deviation in lateral control during cognitive distraction might be mistakenly assumed to be safe driving, resulting in a false negative result.

A study by Liang and colleague [50] observed that combined visual and cognitive distraction resulted in fewer performance errors than did visual or cognitive distraction alone. For example, visual distraction resulted in the highest lane deviation error, followed by visual cognitive distraction and then cognitive distraction. This result indicates the possibility of false-negative detection for both visual cognitive and cognitive distraction. Thus, measures of driving performance do not detect cognitive or visual cognitive distraction very well, despite being excellent tools for investigating the effect of distractions.

B. PHYSICAL MEASURES

Physical measures of the driver are also commonly used for distraction detection. Pohl and colleagues [54] have used head-position and head-pose (the main direction of driver's head) information to model and detect visual distraction. However, they reported that this method has a high potential for false positives. This is because, even if a driver's head is tilted to the side, his eyes could still be looking on the road. The authors acknowledged the importance of eye movements for detecting distraction, and the need for a higher performance eye-tracking device.

An improvement was adopted by Kircher and colleagues [58] by using the "percent road center (PRC)" of gaze direction, which was analyzed over a 1-min epoch. They classified a cognitive distraction as having a PRC larger than 92%, while visual distraction results in a PRC below 58%. Although their method is suitable for offline processing, a 1-min time delay is too long for real-time detection.

Hirayama and colleagues [59] have adopted gaze duration as a detection feature, and have reported a correlation between visual distraction and driving performance. This observation is further confirmed by a study [60] reporting that accuracy of detection using eye-movement data alone is almost identical to that using both driving performance and eye-movement data.

Based on the latest findings, we can conclude that eye-movement features give a good indication of visual and cognitive distraction. Drivers can be said to be distracted when they exhibit frequent fixation and/or longer fixation durations towards a competing task, commonly known as visual distraction. In contrast, longer fixation duration at the same location (either towards a competing task or in the peripheral field of view) indicates cognitive distraction. Although distraction detection has been shown to correlate with driving performance, a combined effect of visual cognitive distraction has only been reported once in a similar study using driving performance [50]. The results indicated that fixation frequency and duration during visual cognitive distraction were lower than under visual distraction alone, and higher than under cognitive distraction alone.

However, for driving to be considered safe, an optimal fixation frequency and duration is required for adequate situational awareness. Therefore, visual and cognitive distraction can be discriminated using eye-movement features if and only if the optimal fixation frequency pattern is identified for each driver.

C. BIOLOGICAL MEASURES

Biological measures such as heart rate information, skin conductance, and electroencephalogram (EEG) have also been used to detect driving distraction. However, studies testing skin conductance and heart rate information showed only a weak relationship between these measures and distraction. Indeed no significant relationship was found between skin conductance [30] or heart rate [30], [61] and driver distraction. Although one study [62] has reported a potential correlation, that experiment was designed to determine the relationship between stress and distraction. As we have defined distraction as related to shifting attention (not stress level),

TABLE 3. The summary of EEG based distraction detection method.

References	Pre-Processing	Feature Extraction	Feature Classification	Distraction Stimuli	Other Measure Used
[63]	Independent Component Analysis (ICA)	Power spectra at frontal, central, parietal, occipital, left motor, and right motor cortices.	Support Vector Machine (SVM)	Mathematical Equation (visual)	• Reaction time • Lateral control
[64]		Nonparametric cluster-based permutation test to detect alpha spindles.	Regularized linear discriminant analysis (LDA)	Auditory task	Reaction time
[65]	ICA	Time-varying autoregressive (TVAR) analysis using Kalman smoother.		Auditory task	
[66]	Gratton method	Singular Value Decomposition (SVD)		Cognitive task (auditory)	• Lateral control • Speed
[67]		Discrete wavelet-packet transform (DWPT) and FFT to determine the spectral centroid and power spectral density.	• Probabilistic Neural Network • K-Nearest Neighbor • Fuzzy Subtractive Clustering	Media player, GPS, mobile phone and SMS	Duration of eyes off the road
[68]	ICA	Event related spectral perturbation (ERSP)		Mathematical equation	Lateral control

further discussion in this section will focus on EEG. Table 3 summarizes findings in the literature regarding how EEG functions in detecting driving distraction.

Generally, EEG is used to measure frontal cortex workload [63]–[68]. For this reason, most distractor stimuli used in the literature are in the form of cognitive distraction such as mathematical equations or auditory tasks. Driving performance measures (lateral control and reaction time) were also used in some studies to validate the EEG findings. The most common pre-processing method was independent component analysis (ICA) and feature-extraction methods were a mixture of spectral features, time-frequency analysis, and event related potential (ERP).

Due to the nature of EEG, measuring participant mental state is very useful and can indicate how sensitive EEG is in detecting cognitive distraction. Taking cognitive load as the indicator, theta and alpha power increases [66] and theta and beta power [68] increases were reported in separate studies. EEG was not reported to detect visual distraction. However, we hypothesize that visual cognitive distraction may be detectable if we use perceptual switching as the indicator.

D. SUBJECTIVE REPORT MEASURES

Subjective measurement is typically used to obtain participant feedback regarding experience or mental workload when driving. The result of this feedback is then compared to the driving-performance measures. Researchers have found that participants score highly on driving-performance measures despite giving themselves a low subjective evaluation [53], [69]. Their awareness of the risks of performing secondary tasks might have influenced their willingness to engage in the distracting tasks [69] or otherwise compensated for their driving behavior. For instance, while there are drivers who tended to reduce the speed of their vehicle while performing secondary tasks [30], [47], [52], other studies have reported increased vehicle speed during distraction due to lack of attention to the speedometer [49], [53]. Combining performance data and subjective measures might succeed in determining the effects of between-subject variability.

Subjective measures also give an overview of the driver's perspective regarding their strategic control as discussed in Regan et al. [70]. The authors state that the strategic decision to engage in a distracting situation depends on the driving culture and associated social perspective concerning acceptable driving behavior. Consequently, realizing the potential risk of distraction is not itself sufficient in preventing accidents due to distraction. Educating drivers on their capability, as well as the potential risks associated with it, might impress drivers to behave more responsibly with respect to safe driving.

There are several ways adopted by researchers to obtain subjective measures. The NASA Task Load Index (TLX) [71], [72] is a standard subjective measure of workload which is commonly used in driving distraction studies [49], [55], [69], [73]. It consists of six standard questions on

TABLE 4. The summary of hybrid based distraction detection method.

References	Driving Performance	Physical	Biological	Machine Learning Methods
[71]	• Lateral Control • Steering wheel (mean & error)	• Eye-fixation duration • Blink frequency • Eye Fixation location		Bayesian Network
[72]	• Longitudinal deceleration • Lateral acceleration • Speed (min, max & % change in speed)	• Eye-fixation duration & frequency • Eye-fixation location • Scan path		
[73]	• Steering wheel (mean & error) • Lateral control	• Eye Fixation • Saccades		Support Vector Machine (81.1%)
[74]		• Eye gaze • Head orientation • Pupil diameter	Average heart rate	• Support Vector Machine (91.7%) • Adaboost (93%)

a 10-point Likert-like scale ranging from 'very good' (10) to 'very bad' (1):

(a) How mentally demanding was the driving task?
(b) How physically demanding was the driving task?
(c) How hurried or rushed was the pace of the driving task?
(d) How hard did you have to work to accomplish your level of driving performance?
(e) How insecure, discouraged, irritated, stressed, and annoyed were you during the driving task?
(f) How successful were you in accomplishing the driving task during driving?

The Rating Scale of Mental Effort (RSME) is another method used to capture self-reported perceptions of mental workload [48], [52]. Similar to NASA-TLX, the responses can be captured only at the end of the experiment. In contrast, the Driver Verbal Protocol is a method that engages the subject while they are carrying out a task [49], [74], [75]. This way, researchers are able to identify the underlying physiological mechanism related to the event as they collect and analyze verbal data about cognitive processing.

Other studies have obtained subjective report measures tailored to their experiment. For instance, in one experiment [76], authors administered interviews to elicit more details about how the driver would react to and interact with various potential distractions, which were later compared with quantitative performance measures. In general, subjective report measures are typically used to complement the objective measures of driving performance in order to get coherent relationships between experimental measurements and causal factors associated with participant behavior.

E. HYBRID MEASURES

Realizing that each of the methods mentioned above has a drawback with respect to certain types of distraction, researchers have begun fusing the methods to create hybrid measures. Most studies listed here utilized hybrid measures with driving performance and physical measures by fusing the responses using machine-learning methods.

Liang and Lee [77] used a Bayesian network to detect distraction based on driving performance (lateral control and the steering wheel) and physical measures (eye-fixation duration, location, and blink frequency). In another study, Weller and Schlag [78] used longitudinal deceleration, lateral acceleration, and speed as driving performance measures, and the same physical measures as Liang and Lee [77]. A support vector machine with an accuracy of 81.1% was used by Liang and colleagues to detect distraction using information from the steering wheel, lateral control, eye fixations, and saccades [79].

A study by Miyaji *et al.* [80] was the only study that used biological measures such as heart rate, and physical measures such as eye gaze, head orientation, and pupil diameter. The study compared detection technique between two machine learning algorithms: a support vector machine and adaptive boosting (Adaboost). They reported an accuracy of 91.7% and 93%, respectively. Even so, both methods were reported as more accurate than other driving-performance measures. Table 4 summarizes the hybrid measures for detecting driver distraction.

Based on our knowledge of the limitations inherent in the measures mentioned above, hybrid measures may indeed increase the robustness and accuracy of detection algorithms.

F. SUMMARY OF DRIVER-DISTRACTION MEASURES

We have discussed each of the five types of measures and recognized its strengths and limitations. Each distraction source can be detected by one or more methods. Table 5 summarizes each method's capability in detecting visual, cognitive, and visual cognitive distraction and its limitations. The data indicate that hybrid measurements have advantages over other methods because any single drawback can be mitigated by evidence provided by one of the other measures.

Combining measures of driving performance and subjective reports requires subjective feedback that can only be obtained at the end of the experiment. Despite being an excellent method for understanding the underlying mechanisms

TABLE 5. Summary of distraction measurements as detection methods.

Distraction Type / Measurement Method	Visual Distraction	Cognitive Distraction	Visual Cognitive Distraction	Advantages	Limitations
Driving Performance	√	X	X	Able to indicate the effect of driving distraction.	• High potential for false response. • Requires complementary subjective reports to obtain high accuracy results.
Driver Physical	√	√	X	Able to distinguish individual types of distraction.	Unable to distinguish a combined type of distraction.
Driver Biological	X	√	?	Able to measure cognitive distraction.	Unable to measure visual distraction.
Subjective Report	X	√	NA	Able to distinguish the underlying mechanism of error.	Requires intervention by researcher.
Hybrid	√	√	?	• Higher accuracy for discriminating types of distractions. • Able to complement the blind spots of other methods	Synchronization of multiple source of data with different sampling rate.

*√ **:** Able to detect, **X:** Unable to detect or potential for false response (Blind spot), **NA:** Not applicable, **?:** Potential for future research*

of error that result from distraction, this process has a substantial drawback if one wants to use automated detection because it requires a third party or a researcher to obtain the feedback.

Physical measures might not be able to distinguish between visual and cognitive distraction. However, by fusing them with biological measures, the hybrid method might compensate and successfully distinguish the type of distraction. For instance, a physical measurement such as eye-movement information might be able to detect visual distraction, but not cognitive distraction because variation in cognitive-related eye movements across drivers is too great, especially at low levels of cognitive distraction. This could lead to false negative results in which the features selected might resemble safe driving if they are not defined accurately. However, biological measurements such as EEG are able to recognize cognitive distraction through brain- features of synchronization, but are not sensitive to visual distraction as this type of distraction mainly involves movement of the eyes towards a specific location. Thus, combining these complimentary measurements should result in a way to accurately determine visual cognitive distraction and its strength.

A potential limitation of this measures is the difficulty to synchronize the data from multiple sources to be used for analysis. This challenge must be address and verified at the data acquisition and pre-processing stage before decision are made based on any detection methods.

Most research in distraction detection focuses on the discrimination between distracted and normal driving. However, sources of distraction can be introduced at varying levels of complexity. For instance, deciphering a GPS map is likely more confusing than reading a simple signboard despite both activities being regarded as competing tasks. Some distractions, such as reading signboard and looking at the GPS, are necessary for driving. However, the distraction level will vary in accordance with the source complexity. Because of distraction levels vary, their effects are predicted to be varied as well. Thus, there is a need to investigate and be mindful of the effects that different levels of distraction have on driving performance to achieve a robust detection method.

IV. CONCLUSION

The statistics for distraction-related driving accidents show a steady increase in frequency, and the percentage of distracted teen drivers was recently revealed to be quite high. In response, scientific focus has been diverted into research on driving distraction. However, a disparity in the reported percentages of distracted drivers is likely due to varying methods of analysis. Thus, a better way is needed to assess distraction in order to suggest appropriate mitigating actions.

We have discussed how each source of distraction may actually involve more than one type of distraction, either visual, cognitive, auditory, or physical. We need to ensure that any measurement method that we use for distraction detection must be robust enough to differentiate these sources of distraction. Additionally, we have to recognize that some of these distractions are necessary for safe driving, such as reading signboards and checking the GPS. Further, source complexity level may cause varied level of distractions.

Driving is known to be a complex task that requires training and a significant amount of driving experience is necessary to be deemed a skilled driver. Thus, experienced drivers should demonstrate better driving performance than a novice driver. This has been shown through statistics. However, driving distraction is defined as shifting attention away from safe driving towards a competing task. Therefore, driving performance for both experienced and novice drivers are affected if drivers are distracted during driving. As a driver's attention is shifted towards a competing task, their situational awareness deteriorates, and they might miss important signals needed for safe driving. In regards to sources of visual cognitive distraction, drivers may be too engaged in the distractor, such as a mobile phone or a confusing sign. This deteriorates the driver's ability to screen the environment, which manifests as poorer perceptual switching.

In order to detect specific types of distraction (such as visual or cognitive), selection of a suitable measurement method is required. We have discussed five common distraction measures: driving performance, physical, biological, subjective reports, and hybrid measures. Among these five, the hybrid measures have an advantage over the other measurement methods in detecting distraction because each component can compensate for the limitations of the other components. Specifically, for developing accurate ways to detect visual cognitive driving distraction, a hybrid method that fuses physical measures (eye movement information) and biological measures (EEG signal) is recommended for future research.

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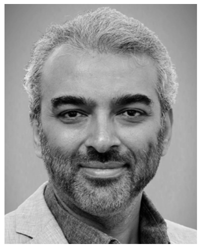

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