Driver Inattention Monitoring System for Intelligent Vehicles: A Review

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***Abstract*—In this paper, we review the state-of-the-art technologies for driver inattention monitoring, which can be classified into the following two main categories: 1) distraction and 2) fatigue. Driver inattention is a major factor in most traffic accidents. Research and development has actively been carried out for decades, with the goal of precisely determining the drivers' state of mind. In this paper, we summarize these approaches by dividing them into the following five different types of measures: 1) subjective report measures; 2) driver biological measures; 3) driver physical measures; 4) driving performance measures; and 5) hybrid measures. Among these approaches, subjective report measures and driver biological measures are not suitable under real driving conditions but could serve as some rough ground-truth indicators. The hybrid measures are believed to give more reliable solutions compared with single driver physical measures or driving performance measures, because the hybrid measures minimize the number of false alarms and maintain a high recognition rate, which promote the acceptance of the system. We also discuss some nonlinear modeling techniques commonly used in the literature.**

***Index Terms*—Distraction, driver inattention, driver monitoring, fatigue.**

I. Introduction

DRIVER inattention is a major factor in highway crashes. The National Highway Traffic Safety Administration (NHTSA) estimates that approximately 25% of police-reported crashes involve some form of driver inattention—the driver is distracted, asleep or fatigued, or otherwise "lost in thought" [1]. One common definition of driver inattention is given in [2]: "Driver inattention represents diminished attention to activities that are critical for safe driving in the absence of a competing activity."

A study by the American Automobile Association Foundation for Traffic Safety (AAA FTS) utilized the following five categories for the driver attention status [3]:

1) attentive;
2) distracted;
3) looked but did not see;
4) sleepy;
5) unknown.

The category "looked but did not see" can be considered a kind of cognitive distraction, and the word "sleepy" could be replaced by the more comprehensive word "fatigued." In this paper, we propose the following two categories for inattention: 1) *distraction* and 2) *fatigue*.

The causes of driver distraction are diverse and pose large risk factors—more than half of the crashes that involve inattention were caused by driver distraction [1], [2]. After an intensive study on the various definitions of driver distraction appeared in the literature, a more general definition is proposed in [2]: "Driver distraction is a diversion of attention away from activities critical for safe driving toward a competing activity."

Thirteen types of potentially distracting activities are listed in [3]: eating or drinking, outside person, object or event, talking or listening on a cellular phone, dialing a cellular phone, using in-vehicle-technologies, and so on. Because the distracting activities take many forms, the NHTSA classifies distractions into the following four categories from the viewpoint of the driver's functionality [1]:

1) visual distraction (e.g., looking away from the roadway);
2) cognitive distraction (e.g., being lost in thought);
3) auditory distraction (e.g., responding to a ringing cell phone);
4) biomechanical distraction (e.g., manually adjusting the radio volume).

Two more categories are added in [2]: 1) olfactory distraction and 2) gustatory distraction. Several distracting activities can involve more than one of these components (e.g., talking to a phone while driving creates a biomechanical, auditory, and cognitive distraction).

The phenomenon of fatigue is different from that of distraction. The term *fatigue* refers to a combination of symptoms such as impaired performance and a subjective feeling of drowsiness [4]. Even with the intensive research that has been performed, the term fatigue still does not have a universally accepted definition [5]. Thus, it is difficult to determine the level of fatigue-related accidents. However, studies show that 25%–30% of driving accidents are fatigue related [6]. In their definition, the European Transport Safety Council (ETSC) states that fatigue "concerns the inability or disinclination to continue an activity, generally because the activity has been going on for too long" [7]. From the viewpoint of individual organ functionality, there are different kinds of fatigue, such as the following cases:

1) local physical fatigue (e.g., in a skeletal or ocular muscle);
2) general physical fatigue (following heavy manual labor);
3) central nervous fatigue (sleepiness);
4) mental fatigue (not having the energy to do anything).

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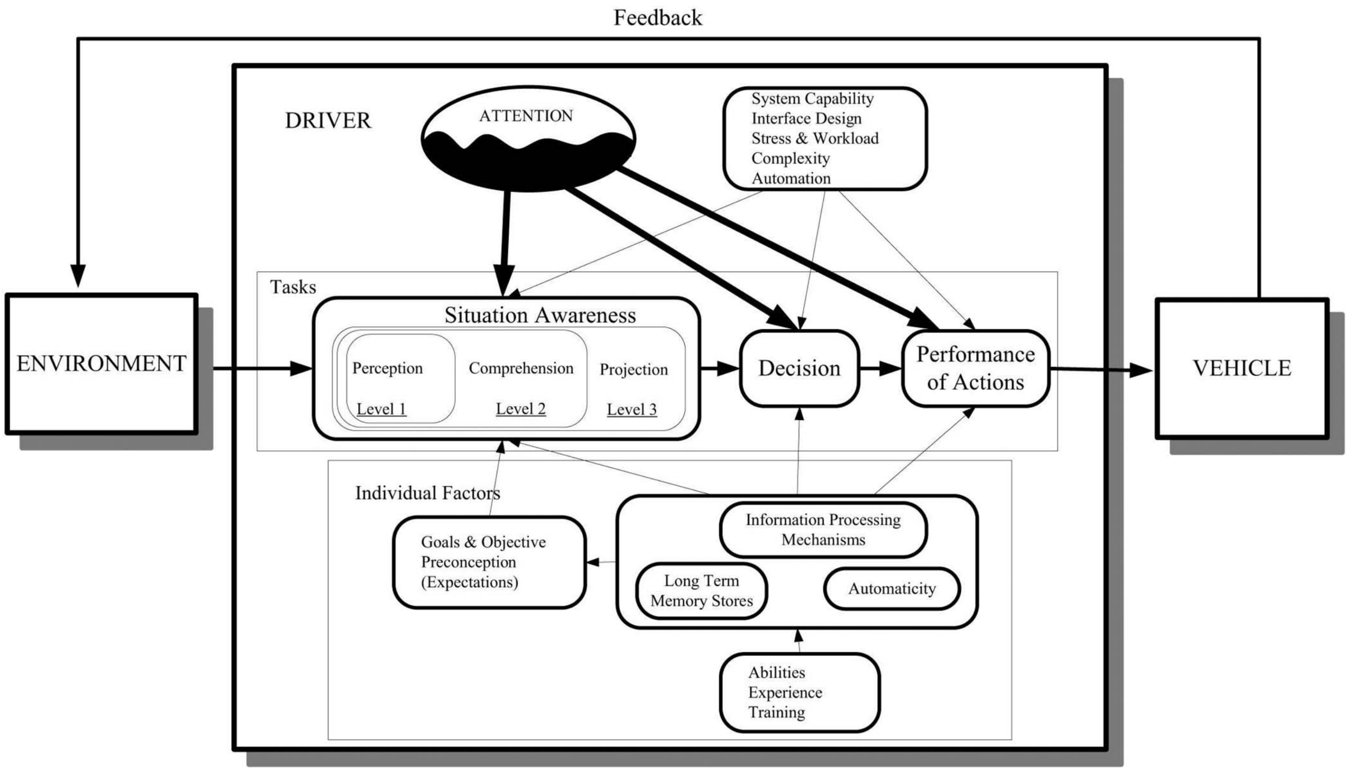


Fig. 1. Information processing and attention [10].

Central nervous fatigue and mental fatigue are the most dangerous types for driving, because these cases will eventually lead to sleepiness, increasing the probability of an accident.

The ETSC defines four levels of sleepiness based on behavioral terms as follows [7]:

1) completely awake;
2) moderate sleepiness;
3) severe sleepiness;
4) sleep.

In an attempt to avoid having an accident, most sleepy drivers will try to fight against sleep with different durations and sequences of the physiological events that precede the onset of sleep [8]. When a driver becomes fatigued and begins to fall asleep, the following symptoms can be observed:

1) repeated yawning;
2) confusion and thinking seems foggy;
3) feeling depressed and irritable;
4) slower reaction and responses;
5) daydreaming;
6) difficulty keeping eyes open and burning sensation in the eyes;
7) lazy steering;
8) difficulty maintaining concentration;
9) swaying of head or body from nodding off;
10) vehicle wandering from the road or into another lane;
11) nodding off at the wheel;
12) breathing becoming shallow;
13) heart races.

Different individuals show different symptoms to varying degrees. Thus, there is no concrete method of measuring the level of fatigue. The ETSC study [7] showed that the level of fatigue or sleepiness (sleepiness is the outside the exhibition of fatigue) is a function of the amount of activity in relation to the brain's physiological waking capacity. Several factors can influence this physiological waking capacity and, hence, lower the fatigue threshold [4], [5], [7], [9], such as disturbed sleep, the low point in the circadian rhythm, and hard work prior to driving. These factors are independent of the activity being undertaken but result in the fatigue effect of that activity appearing more quickly. Thus, fatigue cannot be seen simply as a function of the duration of time engaged in driving.

Driving is a process that involves situation awareness of the environment, decision making, and the performance of actions, as shown in Fig. 1 [10]. In this process, the most complicated stage is the situation awareness. In [10], a three-level situation awareness model is defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future." The deployment of attention in the perception process acts to present certain constraints on a person's ability to accurately perceive multiple items in parallel and is a major limitation on situation awareness. Direct attention is needed not only to perceive and process the available cues but in the later stages of decision making and response execution as well. In a complex and dynamic driving environment, attention demands result from information overload, complex decision making, and the performance of multiple tasks. Thus, monitoring the attention status is vital for maintaining safe driving.

The purpose of the Driver Inattention Monitoring System (**DIMS**) is to monitor the attention status of the driver. If driver inattention is detected, different countermeasures should be taken to maintain driving safety, depending on the types and levels of inattention. **DIMS** has been an active research field for decades. The first international conference on diver distraction and inattention was held in 2009 [11]. A number of auto companies have already installed simple function driver fatigue monitoring systems in their high-end vehicles. However, there is still a great need to develop a more reliable and fully functional **DIMS** using cost-efficient methods in a real driving context. It is believed that the development of signal processing and computer vision techniques will attract more attention to the study of this field in the coming years. With the intention of benefiting individuals or groups interested in or are about to enter this field, this paper gives a comprehensive review of the state of the knowledge on driver inattention. It thus provides a clear view of the previous achievements and the issues that still need to be considered.

This paper is organized as follows. We introduced the driver inattention concept in Section I. Next, the effects of driver distraction and fatigue on driving performance are presented in Section II. Because some commercial products relative to inattention detection have emerged on the market in recent years, Section III is devoted to reviewing these products. Section IV presents a detailed review of the scientific researches on inattention detection. The following five types of measures for inattention detection are presented in this section:

1) subjective report measures;
2) driver biological measures;
3) driver physical measures;
4) driving performance measures;
5) hybrid measures.

After a discussion in Section V, we present a conclusion and propose some areas for future study in Section VI.

II. Distraction and Fatigue Effects on Driving Behavioral Performance

This section concentrates on how distraction and fatigue affect a driver's behavior and driving performance. Exploring these effects could provide useful information for the development of real-time distraction and fatigue detection algorithms.

A. *Effects of Distraction*

Performing a cognitively demanding task while driving influences both the driver's visual behavior and driving performance (as indicated by braking behavior).

1) Driver Behavior Patterns: With an increase in the cognitive demand, many drivers changed their inspection patterns on the forward view. Angell *et al.* [12] indicated that the eye-glance pattern could be used to discriminate driving while performing a secondary task from driving alone and could be used to discriminate high- from low-workload secondary tasks. More facts associated with cognitive distraction driving can be found in [13] and [14]: Drivers narrowed their inspection of the outward view and spent more time looking directly ahead. They reduced their inspection of the instruments and mirrors and reduced their glances at traffic signals and the area around an intersection. Rantanen and Goldberg [14] found that the visual field shrank by 7.8% during a moderate-workload counting task and by 13.6% during a cognitively demanding counting task. Drivers had fewer saccades per unit time, which was consistent with a reduction in glance frequency and less exploration of the driving environment, and in some cases, drivers completely shed these tasks and did not inspect these areas at all [15]. Hayhoe [16] showed links between eye movement (fixation, saccade, and smooth pursuit), cognitive workload, and distraction. Fixations occur when an observer's eyes are nearly stationary. Saccades are very fast movements that occur when visual attention shifts from one location to another. Smooth pursuits occur when an observer tracks a moving object such as a passing vehicle. Saccade distance decreases as task complexity increases, which indicates that saccades may be a valuable index of mental workload [17]. In contrast, the amount of head movement increased when cognitive loads were imposed. It is believed that this condition is a compensatory action by which a driver attempts to obtain a wider field of view [18]. Miyaji *et al.* [18] proposed that the standard deviations of eye movement and head movement could be suitable for detecting the states of cognitive distraction in subjects. Both cognitive and visual distractions caused gaze concentration and slow saccades when drivers looked at the roadway, and cognitive distraction increased blink frequency [19]. Liang and Lee [19] found that visual distraction resulted in frequent long off-road glances. A report from the Safety Vehicle Using Adaptive Interface Technology (SAVE-IT) program showed that eyes-off-road glance duration, head-off-road glance time, and standard deviation of lane position (SDLP) are good measures of visual distraction [20].

2) Other Physiological Responses: When cognitive loads (conversation or arithmetic) were imposed on subjects, pupil dilation occurred by the acceleration of the sympathetic nerve [18]. The average heart rate also increased by approximately 8 beats per minute. However, the average value of the heart rate [R-to-R interval (RRI)] decreased under the same situation [18]. Itoh [21] pointed out that performing a cognitively distracting secondary task (e.g., talking or thinking about something) during driving caused a decrease in the driver's temperature at the tip of the nose, and this effect was reproducible. It was reported in [22] that a considerable and consistent skin temperature increase in the supraorbital region could be observed during cognitive and visual distractions. Berka *et al.* [23] found that the electroencephalography (EEG) signal also contained information about the task engagement level and mental workload.

3) Driving Performance: Significant changes were observed in a driver's vehicle control as a consequence of performing additional cognitive tasks while driving. Ranney [24] found that distraction may be associated with lapses in vehicle control, resulting in unintended speed changes or allowing the vehicle to drift outside the lane boundaries. Zhou *et al.* [25] found the influences on the lane-changing behavior when a secondary task was performed, which included a reduction in the frequency of the checking behavior (check a side mirror or speedometer), a delay in the checking behavior, and a longer time to perform the checking behavior. Carsten and Brookhuis [26] found that the effects of cognitive distraction on driving performance considerably differed from the effects of visual distraction. Visual distraction affects a driver's steering ability and lateral vehicle control, whereas cognitive distraction affects longitudinal vehicle control, particularly car following. Liang and Lee [19] also found that cognitive distraction made steering less smooth but improved lane maintenance. In addition, Liang and Lee [19] found that steering neglect and overcompensation are associated with visual distraction, whereas undercompensation is associated with cognitive distraction. Overall, visual distraction interferes with driving performance more than cognitive distraction. One apparently anomalous finding is that, when secondary task cognitive demands increased, a driver's lateral control ability was found to improve [26]. Harbluk *et al.* [13], [15] found an increased incidence of hard braking associated with cognitive distraction driving.

B. Effects of Fatigue

When a driver is fatigued, certain physical and physiological phenomena can be observed, including changes in brain waves or EEG, eye activity, facial expressions, head nodding, body sagging posture, heart rate, pulse, skin electric potential, gripping force on the steering wheel, and other changes in body activities.

1) Driver Behavior Patterns: Eskandarian *et al.* [27] found that the following actions were correlated with fatigue.

1) Drivers exhibited a reflexive head nod after checking the side mirrors.
2) The head motions were significantly less frequent.
3) The number of times that the drivers touched or scratched their chin, face, head, ears, eyes, and legs significantly increased.
4) Drivers were inclined to turn their head to the left to relieve muscular tension in the neck.
5) Eye-blinking activity radically increased.
6) Episodes of yawning were more frequent.
7) Drivers tended to adopt more relaxed hand positions on the steering wheel.

In particular, for eye-blinking patterns, PERCLOS [28], which is the percentage of time that the eye is more than 80% closed, is one of the most widely accepted measures in the scientific literature for drowsiness detection. It has been validated using both EEG data and subjective evaluation.

2) Other Physiological Responses: The activity of a low-frequency EEG ranging from 0 to 20 Hz has a significant relationship with sleepiness. The spectral analysis of an EEG that shows the transition from wakefulness to sleep can be described as a shift toward slower EEG frequencies. In the alert condition, the appearance of β activity is common in the EEG. α activity is also normally found in the occipital regions (O1 and O2) in the awake and relaxed conditions. When a driver gets drowsy, a burst of α activity can often be seen in the central regions of the brain (C3 and C4). However, some people do not show any α activity. As the driver gets drowsier, the α activity is replaced by θ activity. When δ activity occurs in the EEG, the driver is no longer awake, which is an indicator of deep sleep [29].

3) Driving Performance: It has been reported that sleep-deprived drivers have a lower frequency of steering reversals (every time the steering angle crosses zero degrees) [30], a deterioration of steering performance [31], a decrease in the steering-wheel reversing rate [32], more frequent steering maneuvers during wakeful periods, no steering correction for a prolonged period of time followed by a jerky motion during drowsy periods [33], low-velocity steering [34], large-amplitude steering-wheel movements, and large standard deviations in the steering-wheel angle [35]. Zhong *et al.* [36] found that when drivers had a fatigued status, the steering-wheel angle and vehicle tracking became irregular, and the range of deviation greatly increased. Several researchers found that the lane-tracking ability decreased as the time on the task increased [31]. Variables such as the times of lane departures, SDLP, and maximum lane deviation were found to highly be correlated with eye closures [37]. The mean square of lane deviation, mean square of high-pass lateral position, and SDLP showed good potential as drowsiness indicators [38].

Dingus *et al.* [34] found that the yaw deviation variance and the mean yaw deviation (calculated over a 3-min period) showed some promise as drowsiness indicators. However, no strong correlations between drowsiness and braking or acceleration were found in [34] and [39]. Generally, vehicle speed variability has not shown any strong correlation with drowsiness [39]. However, some reports found that the standard deviation of speed increased from the third driving hour, with a time interval of 45 min [40].

III. Commercial Products and Activities for Driver Inattention Detection

A. Auto Companies

Several famous auto companies are currently conducting researches on driver inattention monitoring systems, including Toyota, Nissan, Volvo, Mercedes-Benz, and Saab.

Saab's Driver Attention Warning System [41], [42] is a project designed to counter the following two most common causes of road accidents: 1) driver drowsiness and 2) distraction. The system utilizes two miniature infrared (IR) cameras: one camera installed at the base of the driver's A-pillar and the other camera at the center of the main fascia, which are focused on the driver's eyes. It also utilizes the SmartEye [43] software to get accurate eyelid, gaze, and head orientation information. In their algorithm, the driver's eye blinking frequency is measured. If a pattern of long-duration eyelid closures is detected, it indicates the potential onset of drowsiness. A three-level warning interface was designed for drowsiness detection. This condition starts with a chime sound and text message, then it moves on to a spoken message, and finally, a stronger warning tone audio message is persistently delivered until the driver presses the reset button. As soon as the driver's gaze moves away from what is defined as the "primary attention zone"—the central part of the windshield in front of the driver—a timer starts counting. If within 2 s of the timer being triggered the driver's eyes and head do not return to the "straight ahead" position, it is considered a distraction. In a case that involves peripheral tasks such as looking in the rear-view mirror, a side mirror, or turning a corner, the timer's elapse time becomes longer. Once the driver distraction has been detected, a seat vibration signal will be issued to warn the driver. However, there is no report about the robustness of this system during daytime and nighttime driving under different kinds of weather conditions, providing no driver status ground truth as a reference.

Toyota developed their Driver Monitoring System in 2006 for the latest Lexus models. This system features a camera, which uses near-IR technology, mounted on top of the steering column cover. It monitors the exact position and angle of the driver's head while the vehicle is in motion. If the Advanced Precrash Safety system detects an obstacle ahead, and at the same time, the Driver Monitoring System establishes that the driver's head has been turned away from the road for very long, the system automatically activates precrash warnings. If the situation persists, the system can briefly apply the brakes to alert the driver [44]. In 2008, the Toyota Crown System went further. It can detect if drivers become sleepy by monitoring their eyelids. Toyota's solution combines driver face orientation and environmental obstacle detection to determine accident potential and utilizes eyelid activity to identify drowsiness.

In the spring of 2009, Mercedes-Benz introduced Attention Assist into its series production [45]. Attention Assist works by first observing a driver's behavior and then uses this information to create a unique driver profile. During operation, a series of tests continually monitor the driver input in relation to this profile, and in the event that a deviation is encountered, the system then determines whether the deviation is a result of fatigue. If it is, Attention Assist both visually and audibly alerts the driver that it is time to take a break. The factors taken into account to determine a driver's profile include the speed, longitudinal and lateral acceleration, angle of the steering wheel, the way that the indicators and pedals are used, certain driver control actions, and even various external influences such as a side wind or an uneven road surface. The Attention Assist system only uses vehicle parameters to determine driver drowsiness, which requires no additional hardware setup. However, this system needs to establish individual profiles for different drivers, which would affect the acceptance of the system in real life.

In 2007, Volvo Cars introduced Driver Alert Control to alert tired and nonconcentrating drivers [46]. With the idea that the technology for monitoring a driver's eyes is not yet sufficiently mature and human behavior varies from one person to another, Volvo Cars developed the system based on the car's progress on the road. It is reported that Driver Alert Control monitors the car's movements and assesses whether the vehicle is driven in a controlled or uncontrolled way. It can also cover situations where the driver focuses too much on his/her cell phone or children in the car, thereby not having full control of the vehicle.

B. Other Commercial Products and Activities

Technological approaches have continued to emerge in recent years and hold promise for detecting and monitoring dangerous levels of driver inattention. Although many of these projects are now in the development, validation testing, or early implementation stages, some companies can provide usable devices or prototypes to give information about driver behavior. For nonintrusive measurement, these devices mainly utilize video cameras and computer vision technologies.

Attention Technology, Inc. has designed and developed the DD850 Driver Fatigue Monitor (DFM): the only real-time onboard drowsiness monitor that is currently tested in an extensive field operational test. The DFM is a video-based drowsiness detection system that works by measuring slow eyelid closure. It is designed to mount on a vehicle's dashboard just to the right of the steering wheel and provides a continuous real-time measurement of eye position and eyelid closure [47]. In particular, DFM estimates PERCLOS to determine drowsiness, which is the proportion of time that the eyes are closed 80% or more over a specified time interval. DFM uses a structured illumination approach to identify the driver's eyes. This approach obtains two consecutive images of the driver using a single camera. The first image is acquired using an IR illumination source that produces a bright-pupil image. The second image uses an IR illumination source at a different wavelength to produce an image with dark pupils. These two images are essentially identical, except for the brightness of the pupils in the images. The third image calculates the difference between these two images, enhancing the bright eyes and eliminating all image features, except for the bright pupils. The driver's eyes are identified in this third image by applying a threshold to the pixel brightness. The bright-pupil effect utilized by DFM is a simple and effective eye-tracking approach for pupil detection based on a differential lighting scheme. However, the success of the bright-pupil technique strongly depends on the brightness and size of the pupils, which are often functions of face orientation, external illumination interference, the distance of the subject from the camera, and race. For real-world in-vehicle applications, sunlight can interfere with IR illumination, reflections from eyeglasses can create confounding bright spots near the eyes, and sunglasses tend to disturb the IR light and make the bright-pupil phenomenon appear very weak.

Delphi believes that computer vision offers the most direct method for detecting the early onset of sleepiness and distraction, and it is also seen as an excellent platform to be shared with other vision-based driver assistance applications in the future. They integrated two products, i.e., the ForeWarn Drowsy Driver Alert and the ForeWarn Driver Distraction Alert, into a comprehensive Driver State Monitor (DSM) [47]. DSM is a computer vision system that uses a single camera mounted on the dashboard directly in front of the driver and two IR illumination sources. Upon detecting and tracking the driver's facial features, the system analyzes eye closures and head pose over time to infer the fatigue or distraction level. It provides an extended eye-closure warning for closures longer than 2.5 s and provides an extended distraction warning for nonforward gaze states in excess of 2.5 s. The fatigue detection algorithm predicts AVECLOS, the percentage of time that the eyes are estimated to be fully closed over a 1-min interval. Because this approach is a less-complex measure of drowsiness than PERCLOS, it permits the use of an automotive-grade data processor, in contrast to the high-grade PC processor required for PERCLOS.

Seeing Machines is engaged in the research, development, and production of advanced computer vision systems for research on human performance measurement, advanced driver-assistance systems, and transportation [48]. Their signature product, i.e., faceLAB, provides head and face tracking, as well as eye, eyelid, and gaze tracking for human subjects, using a noncontact video-based sensor. faceLAB provides comprehensive blink analysis and PERCLOS assessment, including the delivery of raw data on the details of eyelid behavior. Instead of using traditional corneal reflection techniques, input is obtained using a stereo camera pair. Seeing Machines faceLAB has extensively been employed as a PC-based research tool. Although the device reportedly works very well in a simulator environment, the numerous challenges faced in a real driving environment prevent it from robustly working. Seeing Machines also provides another product: Driver State Sensor (DSS). It consists of one camera, two IR light-emitting diode (LED) illuminators, and one special computing and communication unit. The goal of DSS is to detect driver fatigue by analyzing eyelid activity.

Smart Eye AB is another company that provides computer-vision-based software that detects human face/head movement, eye movement, and gaze direction [43]. Their product, i.e., Smart Eye Pro 3.0, is a machine vision system that estimates head pose using a simple and robust method based on tracking individual facial features and a 3-D head model. Although the face is tracked, the gaze direction and eyelid positions are determined by combining image edge information with 3-D models of the eye and eyelids. One major advantage is that eye and head tracking can continue, although one camera is fully occluded or otherwise nonoperational. This approach also allows for large head motions (translation and rotation). Smart Eye has not developed an algorithm that monitors drowsiness.

SensoMotoric Instruments GmbH (SMI) [49] is a German company whose product, i.e., InSight, can measure head position and orientation, gaze direction, eyelid opening, and pupil position and diameter. InSight uses a sampling rate of 120 Hz for head pose and gaze measurement, 120 Hz for eyelid closure and blink measurement, and 60 Hz for combined gaze, head pose, and eyelid measurement. It also provides PERCLOS information for drowsiness detection. It is a computer-based system and needs user calibration.

IV. Current Methods of Detecting Driver Inattention

In the scientific literature, the following five main types of measures for inattention detection are commonly used:

1) subjective report measures;
2) driver biological measures;
3) driver physical measures;
4) driving performance measures;
5) hybrid measures.

With the exception of subjective report measures, these measures are based on nonlinear modeling techniques. In this section, we will briefly review the most common nonlinear modeling techniques. Then, the researches on the five main types of measures will be explored. Finally, the extraction of physical signals from a driver by image processing will be discussed at the end of this section, because driver physical measures offer distraction detection through eye gaze monitoring and fatigue detection through eye gaze, blink, head, and mouth tracking.

A. Nonlinear Modeling Techniques

Human cognition can hardly be represented by a linear model. Hence, nonlinear modeling techniques are greatly adopted in the driver inattention detection area. Nonlinear modeling with machine learning techniques can extract information from noisy data and do not require prior knowledge before training. Some mechanisms in machine learning can avoid overfitting for nonlinear modeling, producing more robust and general models than traditional learning methods (e.g., logistic regression), which only minimize training error.

Artificial neural networks (ANNs) have been studied and utilized in numerous scientific and engineering fields. One of the main advantages of ANNs is that they infer solutions from data with no prior knowledge of the patterns in the data, i.e., they empirically extract the patterns even if the equation between the inputs and outputs does not exist. This characteristic is very important, because in most practical cases, the exact input–output relationship is difficult to establish. ANNs also have the ability to generalize (i.e., they respond with a reasonable accuracy to patterns that are broadly similar to the original training patterns), which is very useful, because real-world data are noisy, distorted, and often incomplete. ANNs are nonlinear, which allows them to more accurately solve some complex problems than linear techniques [27].

The fuzzy inference system (FIS) is famous for its well-known linguistic concept modeling ability. The fuzzy rule expression is close to an expert natural language. A fuzzy system then manages the uncertain knowledge and infers high-level behaviors from the observed data. On the other hand, because it is a universal approximator, FIS can be used for knowledge induction processes [50].

The support vector machine (SVM) is based on the statistical learning technique and can be used for pattern classification and the inference of nonlinear relationships between variables. This method has successfully been applied to the detection, verification, and recognition of faces, objects, handwritten characters and digits, text, speech, and speakers, along with the retrieval of information and images [51]. The learning technique of the SVM method makes it suitable to measure the cognitive states of humans. SVMs can generate both linear and nonlinear models and can compute the nonlinear models as efficiently as the linear ones. Given a set of input data, this method first transforms the input domain through a kernel and then looks for a hyperplane in the transformed domain that separates the data with minimum error and maximum gain. Finally, the hyperplane is transformed back to the input domain to obtain the decision boundaries, which may potentially be nonlinear.

AdaBoost is a learning algorithm that uses the pattern-recognition algorithm called boosting [52]. Its advantages include high classification performance, fast recognition process time, and the potential extension of recognition features. In AdaBoost, learning involves the creation of different classifiers while successively changing the weighting of the learning data. A weighted majority decision is then made for these multiple classifiers to obtain the final classifier function. Individual classifiers are referred to as "weak classifiers," whereas the combination of classifiers is a "strong classifier."

Bayesian networks (BNs) have several advantages that make them well suited for describing human behavior. First, the hierarchical structure of BNs can systematically present information from different sources and at different levels of abstraction and can also capture probabilistic relationships. Second, a BN is not only a computational model but also a form of knowledge representation. Unlike other data-mining approaches such as the SVM, BNs reveal the relationships that generate the model predictions. Third, BNs can handle situations with missing data. The certainty of the hypothesis will change according to the BN's reasoning, which incorporates new data using a probabilistic dependence network when new evidence is added. Because of these advantages, BNs are applicable to human-behavior modeling and have been used to detect inattention [53]. Despite these advantages, creating a correct and stable BN model requires extensive computational capability and a large amount of training data.

Another emerging trend has been to borrow techniques based on hidden Markov models (HMMs) from the speech processing and language technology field and apply these models to driver behavior modeling for route recognition, driver identification, and distraction detection in a manner analogous to speech recognition, speaker identification, and stress detection in speech [54]. The foundation of HMM is a stochastic Markov process that consists of a number of states with corresponding transitions. At discrete time intervals, the Markov process moves from one state to another according to a set of transition probabilities. State changes in the Markov process are hidden from the user. Sathyanarayana *et al.* [54] constructed an HMM using vehicle speed, steering-wheel angle, and braking force to predict route maneuvers (left turn, right turn, and lane change).

B. Subjective Report Measures

The Karolinska Sleepiness Scale (KSS) is the most commonly used tool for the subjective self-assessment of sleepiness; the values used in the KSS are shown in Table I. Kaida *et al.* [55] investigated the validity and reliability of the KSS using EEG, behavioral, and other subjective indicators of sleepiness. Their study showed that the KSS was closely related to EEG and behavioral variables, which indicates that the KSS has a high validity for measuring sleepiness.

Ingre *et al.* [56] verified the close relationship between subjective sleepiness measured with the KSS and blink duration (BLINKD) and lane drifting, calculated as the standard deviation of the lateral position (SDLP) in a high-fidelity moving-base driving simulator. Their experiments showed a significant effect of the KSS on both BLINKD and SDLP. A test for a quadratic trend suggested a curvilinear effect with a steeper increase at high KSS levels for both SDLP and BLINKD.

TABLE I
KSS

KSS	Meaning
1	Extremely alert
2	Very alert
3	Alert
4	Rather alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, no effort to stay awake
8	Sleepy, some effort to stay awake
9	Very sleepy, great effort to keep awake, fighting sleep

Craig *et al.* [57] also found that psychological factors consistently correlated with self-reported fatigue. However, KSS is recorded over relatively long time intervals, e.g., every 15 min, as a tradeoff between high temporal resolution and avoiding intrusive feedback. As a consequence, KSS cannot record sudden drowsiness variations caused by different situations.

C. Driver Biological Measures

Biological signals include EEG, electrocardiogram (ECG), electro-oculography (EOG), and surface electromyogram (sEMG). These signals are collected through electrodes in contact with the skin of the human body. Table II summarizes some typical methods used in this field. EEG has a spatial resolution of 20 mm and a temporal resolution of 0.001 s. It is widely used in the brain activity research field. Recent research has proposed various methods of extracting features from a segment of raw EEG data for fatigue detection. In the time domain, the average value, standard deviation, and sum of the squares of EEG amplitude are the most commonly used features. In the frequency domain, the energy content of each band $(\beta, \alpha, \theta, \delta)$, mean frequency, and center of gravity of the EEG spectrum are commonly used. Other models such as the Auto Regressive Moving Average (ARMA) and power spectrum estimation are also used by some researchers to extract EEG features. The most reliable patterns in terms of their consistency and occurrence for fatigue are the β, α, θ, and δ waves (see Fig. 2).

EEG is widely accepted as a good indicator of the transition between wakefulness and sleep, as well as between the different sleep stages. It is often referred to as the gold standard. Svensson [29] proposed objective sleepiness scoring (OSS), which is derived from EEG signals, as the ground truth for validating other drowsiness detection algorithms. The five-level OSS scores are described in [29] and are shown in Table III.

The four EEG activities (β, α, θ, and δ) were assessed in [58] for 52 subjects during a monotonous driving session. The results showed an increasing trend for the ratio of slow- to fast-wave EEG activities over time. In [59], sample entropy and phase synchronization were adopted to detect fatigue from EEG signals, with the results showing that phase synchronization among the hemispheres gradually increased and sample entropy decreased, both pointing to a gradual increase in sleepiness, which is related to a decrease in EEG complexity. Yeo *et al.* [60] trained SVM to classify EEG signals into four principal

TABLE II
SUMMARY OF BIOLOGICAL MEASURES

Ref.	Bio-signal type	Objective	Analysis methods	Result
[58]	EEG	fatigue	Assess $\delta, \theta, \alpha, \beta$	$(\theta + \alpha)/\beta \uparrow$
[59]			Sample Entropy , Phase Synchronization	Sample Entropy, Phase Synchronization↑
[60]			SVM	predict alert→drowsy
[61]			Probabilistic-SVM	Better than standard SVM
[62], [63]			ICA, FFT, Correlation Analysis, LRM	Est. drowsy level with 87% accuracy
[64]			KPCA algorithm	complexity decreases as fatigue increases
[23]		mental engagement	Inspection with second timescale	Different mental task can be detected
[65]			XCS	Different mental task can be detected
[66]	EEG,ECG	fatigue	dynamic Bayesian network	more features are favorable
[67]	ECG,PPG	PVT	Multi linear regression model	ECG, PPG is useful for est. PVT
[68]	EOG	hypovigilance	8 eye actives, Fuzzy Expert Sys.	Pre. Sleep related accidents with high acc.
[69]	EOG	drowsiness	11 eye actives, SVM	accuracy is quite high for "very sleepy"
[70]	sEMG	fatigue	Statistic analysis	Statistic trends were given
[71]			Frequency and statistic analysis	MDF,MNF,RMS show large change

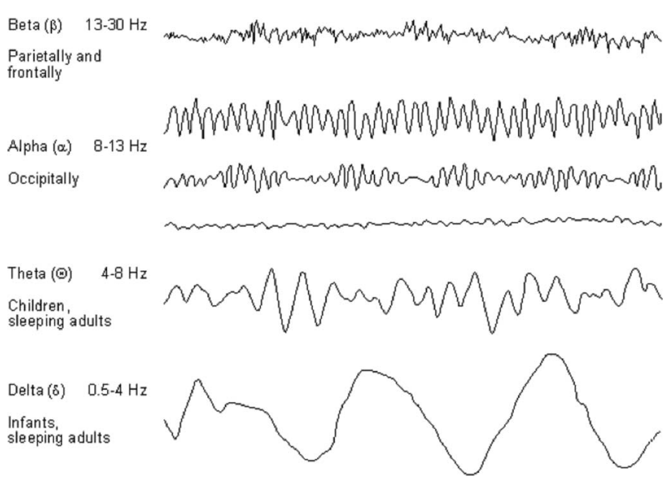


Fig. 2. Four types of EEG waves [29].

frequency bands and then to predict the transition from alertness to drowsiness. Shen *et al.* [61] compared a probabilistic-based and a standard multiclass SVM as classifiers for distinguishing mental fatigue into five mental-fatigue levels and showed that the accuracy of the probabilistic-based multiclass SVM was better. Lin *et al.* [62] established a linear regression model to estimate the drowsiness level from the independent component analysis (ICA) of 33-channel EEG signals and could estimate the drowsiness level with 87% accuracy. They then implemented a real-time embedded EEG-based driver drowsiness estimate system in [63], which adopted only four channels of EEG data.

Although not apparently related, some researches have shown that it is also possible to estimate the distraction level from EEG data. Berka *et al.* [23] tried to use EEG data to continuously and unobtrusively monitor the levels of task engagement and mental workload in an operational environment. An inspection on the EEG data using a second-by-second timescale revealed associations between the workload and engagement levels when aligned with specific task events, which provided preliminary evidence that second-by-second classifications reflect parameters of task performance. Skinner *et al.*

TABLE III
OSS DERIVED FROM EEG DATA [29]

OSS score	EEG content
0	Background of continuous β waves, no α, no θ waves
1	Occurrence of α and/or θ waves, in at least two regions of the brain, for less than a cumulative length of 5 second
2	Occurrence of α and/or θ waves, in at least two regions of the brain, for less than a cumulative length of 5 second or occurrence of α and/or θ waves, in at least two regions of the brain, for more than a cumulative length of 5 second
3	Occurrence of α and/or θ waves, in at least two regions of the brain, for more than a cumulative length of 5 second
4	Continuous α and/or θ waves

[65] investigated the efficacy of the genetic-based learning classifier system known as the accuracy-based classifier system (XCS) in classifying artifact-inclusive EEG signals into four mental tasks designed to elicit hemispheric responses. In [64], the kernel principal component analysis (KPCA) algorithm was employed to extract nonlinear features from the complexity parameters of EEG [approximate entropy (ApEn) and Kolmogorov complexity (Kc)] and improve the generalization performance of an HMM. The result showed that both complexity parameters significantly decreased as the mental fatigue level increased and the classification accuracy reached 84%.

In addition to EEG, other biological signals such as ECG, EOG, and sEMG have also been tested to estimate the mental state of the driver. Yang *et al.* [66] employed a dynamic BN with EEG and ECG to estimate fatigue. A first-order HMM was employed to compute the dynamics of a BN at two different time slices. The results showed that more features are favorable for more reliably and accurately inferring the driver fatigue. In [67], a multiple linear regression model was established to estimate psychomotor vigilance test (PVT) values from a combination of ECG and photoplethysmogram (PPG) data. Damousis and Tzovaras [68] selected eight eye activity features, extracted from EOG, to develop a fuzzy expert system (FES) for the detection of hypovigilance. Hu and Zheng [69] employed an SVM to perform drowsiness prediction with 11 eyelid-related features extracted from EOG. These eyelid features included blink duration, blink duration 50_50, amplitude, lid closure speed, peak closing velocity, lid-opening speed, peak opening velocity, delay of eyelid reopening, duration at 80%, closing time, and opening time. It was reported that the drowsiness detection accuracy was 86% for "sleepy." In [70], the surface sEMG of the shoulder and neck was analyzed while the participant was driving to determine the onset of fatigue and prove that the development of muscular fatigue is a consequence of driving. In [71], frequency and statistical analyses were performed on sEMG signals from the left bicep, right bicep, left forearm flexor, right forearm flexor, and frontal muscles. The results showed that the middle frequency decreased by about 9.5%–18.9%, the mean frequency decreased by about 11.3%–18.4%, and the root mean square amplitude increased by about 25.1%–47.7% from their initial values for a predefined driving route.

D. Driver Physical Measures

1) Fatigue Detection: In [50], PERCLOS, eye closure duration (ECD), blink frequency, nodding frequency, fixed gaze, and frontal face pose were normalized and used as inputs to FIS for fatigue detection. Different linguistic terms and their corresponding fuzzy sets were distributed in each of the inputs using induced knowledge based on the hierarchical fuzzy partitioning (HFP) method. Then, the fast prototyping algorithm with the pruned method (FDT+P) was chosen to automatically generate fuzzy rules that were consistent, lacked redundancy, and were interpretable. Afterward, a simplification process was applied to achieve a more compact knowledge base to improve the interpretability and maintain the accuracy. Finally, three variables (fixed gaze, PERCLOS, and ECD) were determined to be crucial cues for detecting a driver's fatigue. By fusing them with a fuzzy system, a final fatigue detection accuracy of 98% was achieved.

Fan *et al.* [72] utilized a Gabor features representation of the face for fatigue detection. After the face was located, Gabor wavelets were applied to the face area to obtain different scale and orientation features of the face. Then, features on the same scale were fused into a single one to reduce the dimension. Finally, the AdaBoost algorithm was used to extract the most critical features from the dynamic feature set and construct a strong classifier for fatigue detection. It was reported that this method worked well on a wide range of human subjects with different genders, poses, and illuminations.

Friedrichs and Yang [73] explore 18 features of eye movement for drowsiness detection. The features are listed in Table IV. Rather than using principal component analysis (PCA) or linear discriminate analysis (LDA) to reduce the dimension of the features, they chose the sequential floating forward selection (SFFS) [74] algorithm to select the most promising features to construct a classifier. The advantage of SFFS over feature transform techniques is its high transparency, because the selected features remain unchanged. An ANN classifier was trained to detect the drowsiness, and the results showed that, as long as the blinking signals were correctly detected (high confidence), the drowsiness detection accuracy could reach 82.5%.

TABLE IV
EIGHTEEN FEATURES OF EYE MOVEMENT [73]

Features
Average eye closure speed;
Amplitude/velocity ratio (APVC);
APCV with regression;
Blink amplitude;
Blink duration;
BLINKDUR baselined;
Blinking frequency;
Energy of blinking (EC);
EC baselined;
Microsleep event 0.5 s rate;
Microsleep event 1.0 s rate;
Mean square eye closure;
Mean eye closure;
Percentage eyes >70% closed (PERCLOS70);
Percentage eyes >80% closed (PERCLOS80);
PERCLOS70 baselined;
PERCLOS80 EWMA baselined;
Head nodding.

Some other methods have also been used for fatigue detection. In [75], a BN was employed to infer fatigue from gaze information. Orazio *et al.* [76] used a mixture Gaussian model to model the "normal behavior" statistics from the ECD and frequency of eye closure (FEC) for each person to identify anomalous behaviors. Suzuki *et al.* [77] derived the following three factors from the blinking waveform: 1) the length of a blink; 2) the closure rate; and 3) the blink rate. These factors were then weighted using a multiple regression analysis for each individual to calculate the drowsiness level. In [78], the following four cues were fused using fuzzy logic to detect driver fatigue:

1) PERCLOS;
2) head-nodding frequency;
3) slouching frequency;
4) posture adjustment frequency.

In addition to analyzing eye activities, some researches also analyzed mouth activities [79]–[81] to estimate the level of driver inattention. Fan *et al.* [80] used an LDA to classify the mouth into the following two states: 1) normal and 2) yawning. In [81], Vural *et al.* used a BP ANN to estimate the following three mouth states from lip features: 1) normal; 2) yawning; and 3) talking. Vural *et al.* [81] used a facial action coding system (FACS) to code facial expressions and then employed machine learning to discover which facial configurations were suitable for fatigue detection, with 31 facial actions employed to predict drowsiness. This system claimed to predict sleep and crash episodes with a 96% accuracy within subjects and an accuracy above 90% across subjects.

2) Distraction Detection: Kircher *et al.* [82] described and compared two different algorithms for gaze-based driver-distraction detection based on the eye-tracking data obtained in a field study. One algorithm relied on the metric "percent road center" (PRC) of gaze direction, where a PRC of more than 92% was considered indicative of a gaze concentration that results from cognitive distraction, whereas a PRC below 58%, computed over 1 min, was an indicator of visual distraction. Fixations were used for the computation of PRC. The second algorithm was based on a 3-D world model with different interior zones such as the windshield, speedometer, mirrors, and dashboard and on the time that the driver spends glancing at those zones. A time-based "attention buffer" with a maximum value of 2 s was decreased over time when the driver looked away from the "field relevant for driving" (FRD), whereas it was increased when the driver's glance was inside the FRD, until the maximum value was reached. When the buffer reached zero, the driver was considered distracted, and when further conditions were met (direction indicator not activated, speed above 50 km/h, no brake activation, and no extreme steering maneuvers), a warning was issued. The results showed that both algorithms have potential for detecting driver distraction and fully attentive drivers had a PRC of about 70 to 80%.

Pohl *et al.* [83] used head pose and eye gaze information to model the visual distraction level, which was time dependent on the visual focus, with the assumption that the visual distraction level was nonlinear: Visual distraction increased with time (the driver looked away from the road scene) but nearly instantaneously decreased (the driver refocused on the road scene). Based on the pose/eye signals, they established their algorithm for visual distraction detection. First, they used a distraction calculation to compute the instantaneous distraction level. Then, a distraction decision maker determined whether the current distraction level represented a potentially distracted driver.

Bergasa *et al.* [84] tried to detect visual distraction with head pose and fatigue with yawning, eyebrow raising, and PERCLOS. Although they developed an algorithm for extracting the required cues, the algorithm for fusing them was unclear.

E. Driving Performance Measures

A change in the mental state can induce a change in driving performance. In [85], the pressure distribution on the seat of male subjects was measured during simulated long-term driving, and the results showed that there was a relationship between changes in the load center position (LCP) and driver-reported subjective fatigue. Their algorithm for deriving a fatigue index was calculated on a time interval of 10 min, which was a considerable delay.

Farid *et al.* [86] tried to distinguish between attentive and inattentive driving in car-following situations by analyzing the vehicle following distance and steering angle. They built up a real-time model using HMMs with Gaussian mixtures to infer the intentions of the driver, and this model detected a lane change half a second earlier than conventional approaches. Zhong *et al.* [36] performed a localized energy analysis of the steering-wheel angle dynamics and vehicle tracking to detect driver fatigue and found a trend of localized energy increase with driving time. In [87], the chaos theory was employed to explain the dynamics of steering-wheel motion and estimate driver fatigue. Using a proper time delay, Takei and Furukawa found the attractors, which involved the chaos characteristics. They stated that they will study the Lyapunov exponent of this chaos to estimate the driver fatigue. In addition to an energy analysis, in [88], a Gaussian mixture model was adopted to identify the driver based on the following driving behavior signals: 1) forces on the pedals and 2) vehicle velocity.

Torkkola *et al.* [89] adopted the steering-wheel position, accelerator pedal position, lane boundaries, and upcoming road curvature to infer driver status. First, the original signals were preprocessed (averaging and entropy), which yielded a huge set of features. Then, random forest (RF) [90], which is a technique based on ensembles of learners, was employed to select the optimal parameters from the derived features. The classifier was also constructed using RF, and the final accuracy reached 80%.

In [91], a radial-basis neural-network-based modeling framework was developed to characterize normal driving behavior. Then, in conjunction with an SVM, it classified normal and distracted driving. Vehicle dynamics and driving performance data such as vehicle position, velocity, and acceleration, as well as throttle and brake pedal positions, were adopted to model normal driving. The average and standard deviations of the residuals (the differences between the actual and model-predicted driver actions) were chosen as the inputs for the SVM. The results showed that the accuracy varied between individuals.

F. Hybrid

Combining driver physical measures with driving performance measures could intuitively increase the inattention detection confidence. On the other hand, road scene analysis and observations of the driver's face would make it possible to estimate what the driver knows, what the driver needs to know, and when the driver should know it. Combining driver gaze information with road scene information offers the following potential benefits: 1) context relevant information selection; 2) unnecessary information suppression; and 3) anticipatory information selection. Table V shows a summary of some researches that utilized a hybrid method for detecting driver inattention.

1) Fatigue Detection: Eskandarian *et al.* [27] utilized ANN to analyze vehicle parameter data and eye-closure data to infer driver fatigue. The vehicle parameter data included speed, acceleration, vehicle lane position, steering angle, braking, and heading angle, which were recorded at a frequency of 20 Hz. The eye-closure data were recorded at 60 Hz using PC-based

TABLE V
SUMMARY OF HYBRID MEASURES

Ref.	Raw Signals	Fusion Technique	Object
[27]	vehicle parameter data and eye closure data	ANN	Fatigue Detection
[18]	eye gaze, head orientation, diameter of pupils, heart rate (RRI)	SVM and Adaboost	cognitive distraction detection
[92]	leg and head motions, CAN signals	K-Nearest Neighbors classifier	distraction detection
[93]	audio signal and CAN signals	GMM/UBM	distraction detection
[94]	head orientation and the surround salience map	Direct Matching	visual distraction detection
[95]	gaze variables, driving data and road geometry	ANOVA and binary logistic regression	distraction detection
[51]	eye movement and vehicle parameters	SVM	cognitive distraction detection
[53]	eye movement and vehicle parameters	Baysian Network	cognitive distraction detection
[96]	head/eye and vehicle parameters	SVM	visual and cognitive distraction detection
[97]	vehicle and environment parameters	ANFIS	distraction estimation
[98]	eye gaze, blink, head pose and environment parameters	Region Matching	visual and cognitive distraction detection
[99]	head dynamics, facial features, upper body posture information and vehicle dynamics	In Developing	driver assistance

equipment by the Applied Science Laboratory (ASL), which recorded pupil diameter by capturing reflections from the pupils (bright pupil). Then, they analyzed the data to identify the potential variables that were correlated with drowsiness. This analysis found the following four variables highly correlated with fatigue:

1) PERCLOS;
2) vehicle crash;
3) vehicle lateral displacement;
4) steering-wheel angle.

For the simplicity and robustness of the data acquisition, Eskandarian *et al.* [27] implemented two ANN fatigue detectors: One detector utilized the steering-wheel angle signal as an input, and the other detector utilized both the steering-wheel angle signal and the eyelid signal as inputs. The steering angle was preprocessed before being input in the ANN. The preprocessing scheme involved normalization for road curvature, discretization at different ranges, coding, and 15-s accumulation. For the eyelid signal, the preprocessing scheme was the same as in the steering angle, except for eliminating the normalization stage. It was reported that, after proper training and cross validation, the steering-eye ANN had an accuracy of 88%, with a false-alarm rate of 9%, whereas the steering-only ANN had an accuracy of 85%, with a false-alarm rate of 14%.

2) Distraction Detection: In [18], the standard deviations of eye gaze, head orientation, pupil diameter, and average heart rate (RRI) were combined to improve the accuracy of the driver cognitive distraction detection. The eye and head parameters were obtained using faceLAB, whereas the RRI data came from ECG. In [18], two machine-learning techniques, SVM and Adaboost, were implemented under the same conditions. The results showed that the classification performance of Adaboost was slightly better than SVM, whereas the recognition time of AdaBoost was approximately 1/26 of SVM.

Sathyanarayana *et al.* [92] tried to detect distraction by combining motion signals from the leg and head with vehicle signals. The motion signals included the three-axis acceleration of the right leg and two-axis orientation of the head. The vehicle signals adopted included vehicle speed, braking, acceleration, and steering angle. Then, a group of features was derived from these signals based on the nature of the signals. The feature types are listed in Table VI. Next, these derived features were analyzed using LDA to reduce the dimension. Then, a k-nearest neighbor classifier was trained and verified.

TABLE VI
CANDIDATE SIGNAL FEATURES [92]

Signal Features
Maximum value of the signal
Minimum value of the signal
Amplitude of the difference between the first value and the last value
Duration of the signal
Maximum difference between any two consecutive values
Median of the signal
Mean of the signal
Difference between the maximum and minimum value of the signal
Standard deviation of the signal
Root mean square value of the signal
Difference between the max and min value of the differential of signal

To cope with the variability between drivers and maneuvers (context), Sathyanarayana *et al.* [93] utilized a GMM/Universal Background Model (UBM) and likelihood maximization learning scheme to first identify the driver through an audio signal and then recognize the maneuvers (right/left turn and lane change) through controller area network (CAN)-bus signals. Finally, the CAN-bus signals were also used to detect distraction for a particular driver and particular maneuver. It was reported that this system could reach an accuracy of 70% for distraction detection.

Doshi and Trivedi [94] fused head orientation detection and a saliency map of the surroundings to determine whether there was a salient object in the driver's view, which gave an indication of whether a driver's head turn was motivated by the goal in his/her mind or some distracting object/event in the environment.

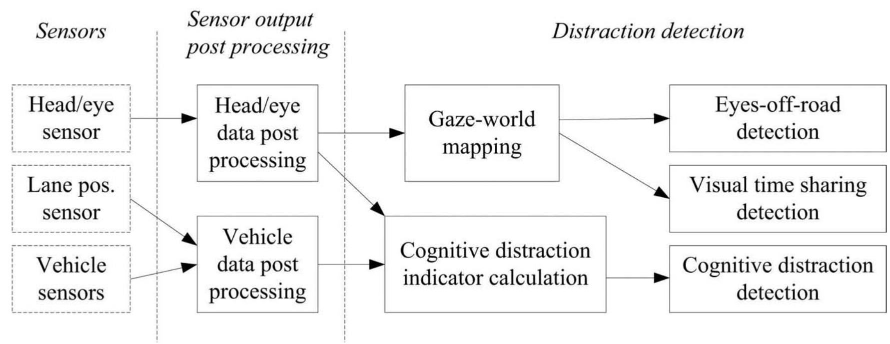


Fig. 3. Overview of the distraction detection algorithms [96].

It is known that road geometry influences gaze behavior [100], and this aspect was taken into account by including road geometry as an additional factor when detecting driver distraction in [95], where Weller and Schlag utilized an analysis of variance (ANOVA) and binary logistic regression to analyze and establish a model for distraction detection based on the following gaze variables and driving data:

1) fixations (number and duration);
2) scan path;
3) standard deviation of gaze location;
4) speed (minimum, maximum, average, and percentage change in speed);
5) lateral acceleration (maximum);
6) longitudinal deceleration (maximum).

The results showed that the road geometry influences the accuracy of distraction detection based on driving data, but gaze behavior is mainly influenced by distraction, with little or no influence by road geometry.

Liang *et al.* [51] tried to detect the driver cognitive distraction caused by interacting with in-vehicle information systems (IVISs) in real time by fusing eye movement and driving performance using an SVM. The measured signals included fixation, saccade, smooth pursuit of the eye (calculated from raw gaze vector obtained using faceLAB [48]), steering-wheel angle, lane position, and steering error. These measures were summarized over various windows to create instances that became the SVM model inputs. After training, the SVM model could detect driver distraction with an average accuracy of 81.1% $(\mathrm{sd} = 9.05\%)$. Lee *et al.* [53] utilized the same conditions as in [51] but adopted a BN to detect cognitive distraction, showing that, compared with an SVM model, the dynamic BN produced better accuracy.

Markkula and Kutila [96] concentrated on processing head/eye and vehicle performance information to estimate both visual and cognitive distractions, and their algorithm is shown in Fig. 3. The head/eye information derived from stereo cameras included head position, head orientation, gaze orientation, saccade, and blink identification, as well as confidence values. The vehicle performance information included lane position and vehicle speed. Based on the head/eye information, they developed gaze-world mapping and eyes-off-road detection, which could detect momentary visual distraction. Another algorithm, i.e., visual time-sharing detection, was developed to measure longer term visual distractions. For cognitive distraction, they used the following three indicators to classify the cognitive tasks with an SVM: 1) the standard deviation of gaze angle; 2) the standard deviation of head angle; and 3) SDLP. However, in the gaze-world mapping phase, which mapped gaze and head angles onto actual real-world targets of visual attention, the road-ahead target was static and determined offline by inspecting the distribution of gaze angles for road-ahead data and then manually enclosing the distribution in a rectangle.

Tango *et al.* [97] proposed a method of deriving the distraction level from relevant vehicle and environment data using the adaptive neuro–fuzzy inference system (ANFIS). Rather than a binary "yes" or "no," they chose reaction time as the output to train, validate, and test their ANFIS model. The candidates to be selected as input for the ANFIS included the environment visibility, traffic density, and the standard deviations in speed, steering angle, lateral position, lateral acceleration, and deceleration jerk. After preprocessing, the level of difficulty of an IVIS and the standard deviation of steering angle were found to have the highest correlations with the reaction time. Thus, they were selected as the input. No accuracy information was provided in [97].

Fletcher and Zelinsky [98] utilized faceLAB to obtain information such as eye gaze direction, eye closure, and blink detection, as well as head position information. In this system, upper and lower bounds were placed on the percentage of time that the driver spent observing the road ahead, which is called the percentage road center (PRC). A percentage that was very high $(> 90\%)$ could indicate a fatigued state (e.g., vacant staring). A percentage that was very low $(< 20\%)$ might indicate a distracted state (e.g., tuning radio). Similar to the PRC metric, they analyzed driver gaze to detect even shorter periods of driver distraction. They used gaze direction to reset a counter. When the driver looked forward at the road scene, the counter was reset. If the driver's gaze diverged, the counter began timing. When the gaze had been diverted for more than a specified time period, a warning was given. The time period for the permitted distraction was a function of the vehicle velocity. As the speed increased, the permitted time period would decrease either as the inverse (reflecting time to impact) or the inverse squared (reflecting the stopping distance). They tried to integrate driver gaze information into other driver assist systems to make the system more acceptable and safer. The framework is shown in Fig. 4. They also spent a significant amount of effort on

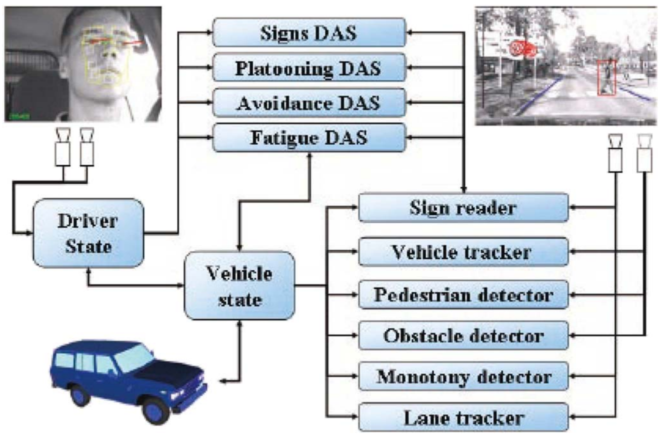


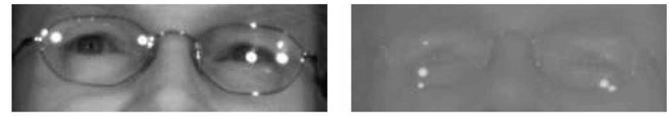
Fig. 4. Distributed modular software architecture [98].

integrating driver gaze information into lane-tracking and sign-reading systems. The lane-tracking system was used to orient the driver gaze information. A strong correlation was found to exist between the eye gaze direction and the curvature of the road during normal driving [101], with a slight correlation being a potential indicator of inattention. Fletcher and Zelinsky [98] integrated driver visual information with sign detection to implement a sign driver-assist system. This system recognized critical signs in the environment. At the same time, the driver monitoring system verified whether the driver looked in the direction of the sign. If it appeared that the driver was aware of the sign, the information could be made passively available to the driver. In contrast, if it appeared that the driver was unaware of the information, it could be highlighted.

A driver's body posture information is potentially related to driver intent, driver affective state, and driver distraction. Tran andTrivedi [99] explored the role of 3-D driver posture dynamics in relation to other contextual information (e.g., head dynamics, facial features, and vehicle dynamics) for driver assistance. It focused on head pose and upper body posture extraction, but no significant results on driver assistance were found.

G. Driver Physical Signal Extraction

Numerous researches have adopted commercial eye trackers to obtain the physical signals related to the face/eye, which have allowed them to concentrate on exploring the inattention detection algorithm rather than image processing. However, these commercial eye trackers can only work well under specific constrained environments. They do not normally work well for real road conditions. For example, Friedrichs and Yang [73] adopted the driver state sensor from Seeing Machines [48] to obtain the eye signal. However, even after many improvements, there were still some issues: Reflections from glasses led to bad signal quality, and varying light conditions during daytime driving posed problems for the eye signal tracking (see Fig. 5). Therefore, much research has been conducted to make the physical signals extracted using image processing more accurate and robust. The methods adopted to extract physical signals are summarized in Table VII.



(a) (b)

Fig. 5. Image processing problems [73]. (a) Reflections on glasses. (b) Bad light due to sun backlight.

For face segmentation in driver inattention detection, the commonly used methods in the literature include a boosted cascade of Haar-like features [102], adaptive boosting [75], landmark model matching [78], skin color [79], and gravity center template [80]. Eren *et al.* [103] adopted stereo cameras and extracted a face from a disparity map on the assumption that the driver's face had a smaller depth than the background. They then used an embedded HMM to recognize the forehead, eyes, nose, mouth, and chin.

After the face area has been segmented, it is necessary to extract the eye and mouth areas for further processing to obtain physical signals. In the literature, the following methods have been employed to extract the eye area. In [102], the eyes were extracted by assuming that they were the darkest regions in the face, [75] located the eyes using a template matching method, [77] used a neural network to detect the eyes, [78] used an edge map to locate the irises of the eyes, and [104] used a p-tile algorithm and k-means algorithm to locate the eyes. In [76], candidate eye regions were first extracted using a modified Hough transform, then symmetric regions in the candidates were chosen as further candidates, and finally, a neural classifier was used to validate the presence of the eye in the image.

Another popularly adopted method for locating eyes involves the use of the "bright-pupil" effect produced by near-IR light. In [50], [105], and [106], a camera equipped with a two-ring IR illuminator was adopted to acquire a driver image. The ring sizes were empirically calculated to obtain a dark-pupil image when the outer ring was turned on and a bright-pupil image when the inner ring was turned on. A controller was designed to synchronize the IR illuminator with the image frame rate, i.e., to ensure that the images with and without bright pupils were interlaced. Digitally subtracting the dark-pupil image from the bright-pupil image produced a difference image, where the pupils appear to be the brightest regions in the image, as shown in Fig. 6. The pupils were detected on the resulting image by searching the entire image to locate two bright blobs that satisfied certain constraints. After locating the eyes in the initial frames, Bergasa *et al.* [50] used two Kalman filters, i.e., one for each pupil, to continuously and robustly monitor a driver with eye closure or oblique face orientation. Huang *et al.* [107] eliminated the need for the synchronizer by acquiring the pupil location from a single image. First, pupil candidates were obtained through Sobel edges, and then, they were identified using an SVM with a Gaussian kernel. In [108], a round-template two-value matching algorithm was proposed for locating bright pupils, which had an accuracy of 96.4% but consumed 1011 ms on a PIII 800-MHz computer.

After the location of the eye is extracted, the blinking and gaze parameters should be calculated. In [102], blinks were

TABLE VII
SUMMARY OF PHYSICAL SIGNAL EXTRACTION

Face Segment	Eye Segment	Blink Feature	Gaze	Mouth Segment	Mouth Feature	Head Pose
boosted cascade of Haar-like features [102], adaptive boosting [75], Landmark Model Matching [78], skin color [79], gravity center template [80], disparity map [103]	darkest regions search [102], template matching method [75], neural network [77], edge map [78], p-tile and k-means algorithm [104], Hough Transform + neural classifier [76], "bright pupil" [50] [105] [106], Sobel edges+SVM [107], Templates Matching [108]	optical flow [102], derivative [77], SVM [78], finite state machine (FSM) [50], Kalman Filtering [105]	Hough Transform and gradient direction [75], Kalman filters and the FSM [50], relative position between pupil and glint [105], pupil features + eigenspace [105], headband+3D eyeball model [106]	fisher classifier [79], gravity center template [80]	connected component analysis to determine lip [79], Gabor wavelet to get mouth corners [80]	two eyes and the center of the face [104], pupil and the nostril position [50], headband [106]

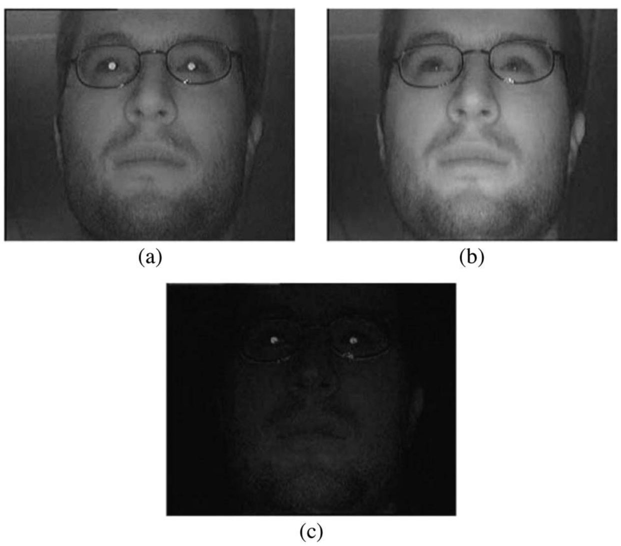


Fig. 6. Fields captured and subtraction. (a) Image obtained with the inner IR ring. (b) Image obtained with the outer IR ring. (c) Difference image [50].

measured by analyzing the optical flow of the eye region. Suzuki *et al.* [77] used a derivative method to detect the eyelids and produce a blinking waveform. Senaratne *et al.* [78] used an SVM to classify the state of the eye as open or closed to get the PERCLOS value. In the "bright-pupil" condition, Bergasa *et al.* [50] implemented a finite-state machine (FSM), with the following five states defined:

1) tracking_ok;
2) closing;
3) closed;
4) opening;
5) tracking_lost.

The transitions between states were achieved from frame to frame as a function of the width/height ratio of the pupils. The ocular parameters such as ECD, PERCLOS, eye closure/opening speed, and blink frequency were calculated as functions of the FSM. Ji and Yang [105] used Kalman filtering to track eyelid movements and compute the PERCLOS and eye closure speed [average eye closure speed (AECS)].

The gaze was estimated by combining the Hough transform and gradient direction in [75], whereas [50] calculated the gaze based on the position and speed data using Kalman filters and FSM. Ji and Yang [105] estimated gaze direction using information about the head movement and relative position between pupil and glint, with the gaze direction quantized into the following nine zones:

1) left;
2) front;
3) right;
4) up;
5) down;
6) upper left;
7) upper right;
8) lower left;
9) lower right.

Cudalbu *et al.* [106] utilized a headband and a simplified 3-D eyeball model to estimate the gaze orientation with an accuracy that varied from 1 to 3°.

In addition to the eye, estimating the position of the mouth is also useful in fatigue detection. Rongben *et al.* [79] used a fisher classifier to extract the mouth area from the face region, whereas Fan *et al.* [80] used a gravity center template to extract the mouth area. Then, Rongben *et al.* [79] used connected component analysis to find the lips and Fan *et al.* [80] used a Gabor wavelet to get the corners of the mouth.

The head-nodding frequency, slouching frequency, and posture adjustment frequency were derived from changes in the head position in [78]. Su *et al.* [104] clustered facial orientations into five clusters—frontal, left, right, up, and down—depending on the position of the eyes and the center of the face. Similarly, based on the pupil and nostril positions, Bergasa *et al.* [50] made a coarse 3-D face pose estimation. Ji and Yang [105] used an eigenspace algorithm to map seven pupil features (interpupil distance, sizes of the left and right pupils, intensities of the left and right pupils, and ellipse ratios of the left and right pupils) to determine face orientation, which was quantized into the following seven angles:

1) $-45°$;
2) $-30°$;
3) $-15°$;
4) $0°$;
5) $15°$;
6) $30°$;
7) $45°$.

Cudalbu *et al.* [106] employed a headband with IR reflective markers to estimate the 6-degree-of-freedom head pose with an average error of 0.2°.

V. Discussion: Issues and Systematical Design Consideration

A. Issues With Detection

The subjective report measures can produce some reasonable results in quantifying the fatigue level. Because this kind of approach requires that the driver frequently report his/her state, both the fatigue level result and the driver could cause interference. Large individual differences have been observed with the overall driving performance and blink duration independent of the KSS values [56]. In addition, Schmidt *et al.* [109] demonstrated that drivers have difficulty judging their fitness, particularly after about 3 h of continuous monotonous daytime driving with increasing drowsiness. For these reasons, it is not sufficient to solely record the KSS. However, if only a rough fatigue level is needed and the lowest cost is required, this kind of approach may be the best choice. The driver biological measures directly measure biological signals from a driver's body and have been found to be highly accurate when used to detect a driver's fatigue level. Svensson [29] even proposed an OSS method that relied on EEG. However, most of the driver biological measures are intrapersonal. The results in [71] showed that intrapersonal data had a good linear trend, whereas interpersonal data showed a different threshold. Bouchner [110] also showed that the EEG was very dynamic and very sensitive to outside factors. In addition, EEG patterns vary between individuals. Therefore, these two kinds of measures should be treated as rough ground-truth indicators for other methods. Driver physical measures and driving performance measures are the most promising methods in the real driving context, because neither relies on intrusive measurements that might affect the driver.

For fatigue detection, the most popularly used parameter in driver physical measures is PERCLOS. However, one of the limitations of PERCLOS is that its prediction is good only when using large time intervals. Moreover, PERCLOS does not take into account the variability in human behavior, because the blinking activity can significantly differ between individuals. Another challenge for driver physical measures is the robustness of the algorithm under all driving conditions (day and night, sunny and cloudy, and so on), because this type of method mainly relies on image processing. Many researchers have adopted IR illumination techniques in image acquisition systems for three purposes. First, they minimize the impact of different ambient lighting conditions. Second, they allow the bright-pupil effect to be produced, which makes eye detection easier. Third, because near-IR is barely visible to the driver, it minimizes any interference with their driving. The "bright-pupil" effect benefits the eye-extraction process, but it only works well under some constrained lighting conditions. Moreover, in real driving scenarios, these constraints cannot be satisfied most of the time. In [50], the following three main illumination challenges were encountered, as shown in Fig. 7: 1) artificial light from elements outside the road (such as street lights); 2) vehicle lights; and 3) sunlight. The "bright-pupil" effect will disappear under these conditions, which causes the eye detection to fail and consequently influences the inattention detection. For example, sunlight and reflections from glasses could cause the performance to considerably drop to 30% [50]. Regardless of how the hardware is adjusted, the "bright-pupil" effect is not robust, particularly in daytime [50] or when wearing glasses [27]. Even under constrained conditions, the reflection of the IR in the pupils varies by individual. Even with the same driver, the intensity depends on the gaze point, head position, and opening of the eye. Therefore, more reliable real-time eye-detection algorithms are preferred over the "bright-pupil" effect. As described in Section IV-G, most studies have concentrated on image processing and have quite roughly estimated the driver physical parameters (e.g., gaze, face pose, and mouth activity). Combining the image processing with some face mathematical models leads to more accurate estimation. Dong *et al.* [111] developed a real-time tracking kernel for stereo cameras to estimate face pose and face animation, including the movement of the eyelid, eyeball, eyebrow, and mouth, for driver inattention detection.

(a) (b) (c) (d)

Fig. 7. Effects of external lights on the acquisition system. (a) Out-of-the-road lights effect. (b) Vehicle lights effect. (c) Sunlight effect. (d) Sunlight effect with filter [50].

The advantage of driving performance measures is that the signals are meaningful and readily available. Moreover, the literature shows that they are useful for estimating driver fatigue and show good promise in a real driving context. Although, in Section II-A, we showed that many researchers have found that driver distraction influences driving performance, few studies have utilized driving performance measures to detect distraction, with most researchers concentrating, instead, on fatigue or abnormal detection.

One more issue that should be pointed out is that many of the researches claimed very high detection accuracies, which were true only for their particular hypothetical fatigue/distraction definitions. These hypothetical definitions usually covered a limited region of the whole fatigue/distraction definition. Without this condition, the accuracy rates had no meaning.

Because of the significant difficulties inherent in measuring driver attention, the magnitude and, particularly, the safety implications of driver distraction have been very difficult to determine. Indeed, unlike seat belt use, the driver's attention status cannot be categorized as "yes" or "no" but should be quantified in the same manner as blood alcohol level [24].

The factors that influence driver fatigue/drowsiness include greater daytime sleepiness, less sleep, a more difficult schedule, more hours of work, age, driving experience, cumulative sleep debt, the presence of a sleep disorder, and the time of day. This paper has focused on real-time inattention detection technology rather than on long-term sleep/wake regulation prediction technology. Biomathematical models that quantify the effects of the circadian and sleep/wake processes on the regulation of alertness and performance have been developed in an effort to predict the magnitude and timing of fatigue-related responses in transportation operations. These models of fatigue and performance typically use input information about sleep history, duration of wakefulness, work and rest patterns, and the circadian phase to predict sleepiness, performance capability, and/or fatigue risk [47]. Research on biomathematical models could enhance the confidence of the real-time estimation, because the former could be used to predict when the probability of sleepiness will become higher. For descriptions of these biomathematical models, see [47].

B. Systematical Design Consideration

This paper has indicated that no single measure can be used to reliably detect inattentive driving. A combination of different measures is recommended, e.g., analyses of lateral control performance and eye blink patterns. According to the definition of driver distraction [2], when driver distraction occurs, there should be some kind of distraction source that exists inside or outside the vehicle. Therefore, fusing driver gaze information and vehicular ego state (steering, lane position, speed, and state of IVIS) with the current road scenario (e.g., the type of road, weather conditions, and traffic density) will lead to a more comprehensive understanding and recognition of driver distraction.

The level of distraction associated with a given secondary task depends on the extent to which a driver is engaged in the task. Different secondary tasks have different requirements for concentration. Thereby, they have different levels of distraction. Based on the number of button presses and/or glances away from the forward road, Klauer *et al.* [112] defined the following three categories of secondary tasks: 1) complex tasks; 2) moderate tasks; and 3) simple tasks. It was found that complex tasks carried three times the risk of involvement in a crash or near-crash as simple tasks or no secondary tasks. In particular, for drivers who perform complex secondary tasks, elevated likelihood ratios were found for the following conditions:

1) dusk and unlighted darkness;
2) rain;
3) divided roads;
4) roads with grades (straight or curved).

Therefore, identifying the environmental conditions is important to correctly assess the risk of the distraction.

Different environments contribute different risk levels for the same inattention state. Different environments could also induce the occurrences of different distractions. In particular, [3] reported that crashes associated with adjusting audio devices were more likely at night, crashes associated with moving objects inside the vehicle were more likely on nonlevel grades, and distractions that involve communication with other occupants were more likely at intersections. Horne and Reyner [113] found the following criteria associated with drowsiness-related accidents:

1) the vehicle running off the road;
2) no sign of braking;
3) no mechanical defect;
4) good weather;
5) the elimination of speeding.

The NHTSA [27] reported the following indirect cues: 1) Accidents were more likely to be associated with the period from midnight to early morning, 2) rural highways with a speed limit of 55–65 mi/h, and 3) fixed objects (trees, guardrail, and highway signs). Thus, if these contextual cues could be taken into account when determining the risk level of an inattention occurrence and determining which countermeasure should be adopted, it would make the driver inattention monitoring system more reliable and acceptable.

VI. CONCLUSION

In this paper, we have reviewed the current state of the knowledge about driver inattention monitoring. Driver inattention increases driving risk and has become a major factor in a considerable percentage of traffic accidents. Driver inattention has no universally accepted definition. However, based on a review of the literature, we classify driver inattention into two main categories—distraction and fatigue—each of which also contains a few subcategories. In summary, distraction means that drivers can pay attention, but their attention is shifted away from the primary driving task to some secondary task or attracted by some attractive object/event. Fatigue means that drivers have exhausted their attention energy and cannot maintain sufficient attention to driving. The causes of distraction and fatigue are different, and they impose different influences on the driver and driving performance. Revealing these influences could help when selecting appropriate measures to develop a real-time inattention monitoring system. Recently, many commercial products relative to driver inattention monitoring have emerged. Auto companies such as Toyota, Nissan, Volvo, Mercedes-Benz, and Saab have installed driver inattention monitoring systems on their top-brand vehicles and/or are conducting researches on such systems. A few third parties, e.g., Seeing Machines and SmartEye, provide camera-based nonintrusive tools for measuring driver physical signals such as gaze, head pose, and mouth activity. It should be pointed out that, in most cases, neither the scientific and technological method behind nor the exhaustive results of the performance can be provided for these commercial products.

Several articles have reported that these tools work well under constrained conditions but are not robust under real driving conditions. Thus, there is still much progress to be made to improve the robustness and accuracy of the physical measuring tools. In the scientific literature, the following five types of measures could be found to detect driver inattention:

1) subjective report measures;
2) driver biological measures;
3) driver physical measures;
4) driving performance measures;
5) hybrid measures.

Although it is not suitable for a real-life context, subjective report measures and driver biological measures could serve as some rough ground-truth indicators. Because driver physical measures and driving performance measures have advantages and disadvantages, hybrid measures are believed to provide more reliable solutions, which will both accurately detect driver inattention and minimize the number of false alarms to promote the acceptance of the system. After all, the goal of a driver inattention monitoring system is to reduce driving risk. To obtain this goal, the following three distinct sources of data should be combined: 1) driver physical variables; 2) driving performance variables; and 3) information from the IVIS. In addition to these variables, it is important to consider the characteristics of the driving environment (e.g., the type of road, weather conditions, and traffic density).

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