Driver Behavior Analysis for Safe Driving: A Survey

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***Abstract*—Driver drowsiness and distraction are two main reasons for traffic accidents and the related financial losses. Therefore, researchers have been working for more than a decade on designing driver inattention monitoring systems. As a result, several detection techniques for the detection of both drowsiness and distraction have been proposed in the literature. Some of these techniques were successfully adopted and implemented by the leading car companies. This paper discusses and provides a comprehensive insight into the well-established techniques for driver inattention monitoring and introduces the use of most recent and futuristic solutions exploiting mobile technologies such as smartphones and wearable devices. Then, a proposal is made for the active of such systems into car-to-car communication to support vehicular ad hoc network's (VANET's) primary aim of safe driving. We call this approach the dissemination of driver behavior via C2C communication. Throughout this paper, the most remarkable studies of the last five years were examined thoroughly in order to reveal the recent driver monitoring techniques and demonstrate the basic pros and cons. In addition, the studies were categorized into two groups: driver drowsiness and distraction. Then, research on the driver drowsiness was further divided into two main subgroups based on the exploitation of either visual features or nonvisual features. A comprehensive compilation, including used features, classification methods, accuracy rates, system parameters, and environmental details, was represented as tables to highlight the (dis)advantages and/or limitations of the aforementioned categories. A similar approach was also taken for the methods used for the detection of driver distraction.**

***Index Terms*—Car-to-car communication, driver behavior dissemination, driver fatigue detection, driver inattention monitoring, smartphone, wearable devices.**

I. Introduction

In the last decade, the number of improvements for driver safety has been more than ever yet a significant number of serious accidents still occur all over the world. Those are mostly caused by human mistakes, such as typing a text message, speaking someone on the phone, eating and drinking etc., while driving. In addition to these activities, drowsiness, sleepiness or distraction could also result in critical and harsh accidents. According to The Large Truck Crash Causation Study, 13% of crashes involving heavy commercial vehicles are occurring because of the driver's tiredness [1]. As reported by the U.S. National Highway Traffic Safety Administration every year approximately 60,000 traffic accidents take place due to sleepiness related problems [2]–[4]. Also, up to 20% of road accidents in UK are based on the aforementioned reasons [5], [6]. It is not only the drowsiness of a driver, which is a major factor beyond the traffic accidents, but also driver distraction is another threat for drivers' and passengers' safety [7], [8]. Previous studies indicate that 25%–30% of driving accidents are related to drowsiness [9].

Traffic accidents can cause physical, financial and mental damages for everyone involved. Drivers and passengers can suffer from minor cuts and bruises to broken limbs, whiplash, back and spinal injuries, paralysis and even death. Vehicles in traffic accidents are damaged and may be in need of minor or costly repairs or may even be wreckage and no longer drivable [1]–[6].

Statistical data given by British and American crash reports show us that avoiding driving during drowsiness and/or distraction is extremely important approach to prevent such serious accidents. Governments legalized some policies to decrease the number of accidents, such as the mandatory rest in long-distance driving. However, these precautions are still not enough to reduce the rate of those accidents. Therefore, in order to prevent vehicle accidents, researchers aim at systems to monitor drivers and to measure the distraction level of drivers. These kinds of systems are broadly called Advance Driver Assistance Systems (ADAS), Driver Inattention Monitoring Systems, and Driver Alert Control Systems [9]–[12].

All in all, drowsiness and distraction are the two subjects of the study that researchers have been focused on for designing driver inattention monitoring systems. Systems designed for the analysis and detection of drowsiness can be broadly divided into two categories: *visual features based and non-visual features based*. Techniques using visual features take advantage of computer vision approaches for the detection of drowsiness. Exploiting visual features focuses on extracting facial features like face, eyes and mouth. Analyzing the state of eyes and mouth can provide observable cues for the detection process. Mainly, techniques using visual features can be divided into four categories: *eye state analysis, eye blinking analysis, mouth and yawning analysis and facial expression analysis*. Image processing and machine learning techniques are the two main steps for detecting and processing visual features. Techniques based on non-visual features are generally intrusive and can be divided into two categories: *driver physiological analysis and vehicle parameter analysis*. For example, in the EEG technique, multiple sensors need to be attached to a driver while driving. Using typical driving data such as the movement of the steering

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wheel or the pressure exerted on the brake pedal also provides reliable information. Similarly, systems for the detection of distraction are based on computer vision too. For example, the two common methods, analysis of head movement and gaze, enable an early detection of driver distraction to avoid accidents.

The main contribution of this paper could be given as follows:

- Elaboration on the recent use of mobile solutions including smartphone applications and wearable devices for safe driving.
- Extension of vehicular ad hoc network's (VANET's) primary purpose of driving safety by using our proposed concept of "driver behavior dissemination" via C2C communication.

The organization of this paper is as follows. In Section II, we first introduce fatigue expressions and then discuss fatigue detection techniques and methods. Section III describes driver distraction techniques, in particular, head pose and gaze direction methods. In Section IV, we introduce the studies and applications, which enable mobile technologies for driver safety. In Section V, we propose a new concept, driver behavior dissemination for safe driving, and discuss the futuristic solutions based on VANET. Section VI explores detailed review of each technique with (dis)advantages and limitations. Besides, this section discusses hybrid solutions for safe driving in terms of driver monitoring systems. We also introduce open issues and challenges related to driver monitoring systems for safe driving.

II. Driver Fatigue Detection Techniques

Human fatigue expressions are highly important to understand the behavior of drowsy drivers. Fatigue is a term used to describe the general overall feeling of tiredness and/or a lack of energy [13]. It also refers to as drowsiness, exhaustion, lethargy, and listlessness and it describes a physical and/or mental state of being tired and weak. Although physical and mental fatigues are different from each other, the two often exist together - if a person is physically exhausted for long enough, he/she will also be mentally tired. When somebody experiences physical fatigue, it means he/she cannot continue functioning at his/her normal levels of physical ability. Mental fatigue, however, is more slanted towards feeling sleepy and being unable to concentrate properly.

It is important to understand that fatigue is not a disease and could be overcome by taking a rest or sleeping. However, fatigue may cause serious accidents especially while a person is driving a car, a bus, a railroad train or other vehicles that require constant attention [1]–[6].

There are many researches and studies trying to understand physiological mechanism of human fatigue/drowsiness and how to measure the level of fatigue [14]–[16]. Based on such studies, many active safety systems have been developed to monitor human drowsiness or fatigue [17]. These studies show us that human fatigue generation is very complicated and complex process and many factors affect fatigue in different ways.

In this section, we first categorize human fatigue expressions based on A Dynamic Bayesian Network for Fatigue Modeling [18]. A Bayesian Network (BN) is a state-of-the-art knowledge representations scheme dealing with probabilistic knowledge. There are several uncertainties for human fatigue generation. First of all, fatigue is not observable and can only be inferred from the information [19]. It is believed that fatigue can be related to as a result of many contextual variables such as working environment, health, sleep quality, and the cause of many symptoms, e.g., the visual cues, such as irregular eyelid movement and yawning. Second, the characteristic of visual cues of a human being varies with age, height, health and shape of face. To effectively monitor fatigue, a system that systematically represents and integrates various sources of information related to fatigue over time, is necessary. Fatigue can be understood from the following reactions of human.

Facial Expressions: A drowsy person can be detected from his/her facial expressions such as yawning, happiness, and anger. Drowsy person will have less facial expressions and exhibit more frequent yawning.

Head Movements: A drowsy person can be detected from his/her head movements. Drowsy person will exhibit certain unique head movement such as head nodding.

Gaze (Pupil) Movements: A drowsy person can be detected from his/her gaze pupil movements. It is observable that drowsy person has a narrow gaze region than when they are alert. Also drowsy person has less saccadic movements than when they are alert.

Eyelid Movement: A drowsy person can be detected from his/her eyelid movements. It is observable that drowsy person will blink distinctly slower than when they are alert. Besides, drowsy person will close his/her eyes for a longer time than when they are alert. To make it simple, drowsy person has longer eye closure duration than the alert person.

Drowsiness of a person manifests itself in physical and physiological changes which can either be visually observed by his/her eye and/or mouth activity, head nodding or can be digitally registered via EEG and/or heart rate monitoring. Therefore, we can safely categorize methods for fatigue detection into visual and non-visual methods based on the features used. Several studies including the recent ones are thoroughly examined and proposed methods, features used for classification along with the respective classifiers, limitations, (dis)advantages and accuracy of the methods as well as their experimental setup are given in Table I.

A. Techniques Based on Visual Features

There are several studies that used computer vision methods to detect driver drowsiness shown as in Table I. Especially, studies, which focused on facial expressions, take advantage of computer vision methods since it is easy to understand from his/her facial expressions whether a driver is sleepy or awake. The eye state, eye blinking frequency, mouth state and yawning frequency of a driver are the key factors for detecting drowsiness [39]. Eye closure duration is the important parameter for detecting driver drowsiness. Systems that use this technique usually monitor eye states and the position of the iris through a specific time period to estimate the eye blinking frequency and the eye closure duration. For those systems,

TABLE I
THE LIST OF MOST REMARKABLE AND LEADING SOLUTIONS FOR DRIVER DROWSINESS DETECTION

			Technique	Ref. No	Year J-C	Accuracy	Parameters (Sampling Rate)	Methods	Classifier(s)/ Feature(s)	System Implementation	Advantages	Disadvantages	Limitations
DD	VF	CV	Eye Condition Analysis (Eye Open/Close Duration-Eye Blink Rate)	[21]	2010 J	94	110 fps	Viola Jones Algorithm, PERCLOS, STASM	Haar-like	Intel Xeon 2.9 GHz CPU, OpenCV	Robust, Non-intrusive	High computation time	Sunglasses, Varying lighting conditions
				[22]	2012 C	98.4	30 fps	Local Binary Pattern, Viola Jones Algorithm, AdaBoost	SVM, Haar-like	Intel Core 2 Duo 2.8 GHz CPU 4 GB RAM, Matlab7.8.0.347	Ease of use, Reliable, Non-intrusive	Computational complexity	Sunglasses
				[23]	2014 J	80	18 fps	Viola-Jones Algorithm, AdaBoost PERCLOS	SVM, LBP	Intel P4 2.1 GHz CPU 2GB Memory, Microsoft Visual Studio 2010, OpenCV	Real-time, Reliable, Non-intrusive	Computational complexity	Glasses, Sunglasses
				[24]	2014 J	97	24 fps	Window Growing, PERCLOS	HOSVD	Pentiumsi7 Q 820 1.73 GHz 8 GB RAM Two cameras and LED, HIL library	Reliable, Robust	Intrusive, Complexity	Sunglasses
				[25]	2014 J	95	30 fps	AdaBoost, PCA and LDA, PERCLOS	SVM	Intel Pentium-M 1.60 GHz 500 MB RAM, Visual C++	Robust, User identification, Non-intrusive	High computation time	Sunglasses
			Mouth and Yawning Analysis	[26]	2008 J	81	N/A	Viola-Jones Algorithm, AdaBoost, RBF Kernel	SVM	N/A	Non-intrusive, Reliable	Computational complexity	Varying lighting conditions
				[27]	2010 J	91	N/A	Kalman Filter, HSV Space, Morphological Operations, YCbCr Method	N/A	Matlab	Non-intrusive, Less complex	Expensive to install	Varying lighting conditions, Skin types
				[28]	2011 J	80	30 fps	Hidden Markov Models, Discrete Wavelet Transform	Naive Bayes SVM	APEX smart camera Systems, OpenCV	Feasible, Less complex, Non-intrusive	Need extra equipment	Having beard, Varying lighting conditions
				[29]	2012 J	60	30fps	Viola-Jones Algorithm, Adaboost	SVM, Haar-like	ARM926EJTM 350MHz 16MB DDR SDRAM, APEX smart camera systems, OpenCV	Reliable, Embedded system, Real-time	Computational complexity	Limited embedded smart camera platform
				[30]	2014 J	80	N/A	YCbCr Color Space, Canny Edge Detector	Haar	Matlab	Non-intrusive	Not realistic	Limited implementation, Varying lighting conditions
	NVF		EEG Signals	[31]	2005 J	88.2	Low-pass filter with a cut-off frequency of 50 Hz Sampling rate of 500Hz	Electroencephalogram (EEG), Independent component analysis (ICA), Heart-rate variability (HRV)	N/A	VR-based dynamic driving simulation, EEG/EOG sensors	Fast, Reliable, Realistic, Feasible	Intrusive, Expensive, Large system, Power consumption	Limited platforms, Limited EEG channels
				[32]	2010 J	88.7	Low-pass filter with a cut-off frequency of 32Hz Sampling rate of 512Hz	EEG, Fast Fourier Transform, Mahalanobis Distances	N/A	VR-based cruising environment	Fast, Reliable, Less power consumption	Intrusive	Improper electrode contact
				[33]	2010 C	N/A	Sampling frequency 1000Hz	EEG, Fast Fourier Transform, Fast ICA	N/A	NT9200 Instrument	Reliable, Fast	Intrusive, Wired, Not miniature	Ineffective signal measurement
				[34]	2012 J	N/A	N/A	EEG, Pulse-Width Modulation (PWM)	N/A	Signal processing unit, PIC micro controller, Alarm, Max232 PC, LCD	Fast	Intrusive, Hardware complexity, Wired transmission	Micro electrodes
				[35]	2014 J	97	Sampling frequency 1000Hz	EEG, Fourier Transform, Power Spectrum Density Features	Artificial Neural Network (ANN)	Four flickering white LEDs, ProComp Infiniti™ device	Feasible, Robust, Short time detection	Intrusive, Not realistic	Micro electrodes
			Vehicle Movements	[36]	1994 J	77		Binarization, Noise Removal, Median Filter	N/A	CRT monitor, Infrared lamp, Sensors, Alarm	Feasible	Intrusive, Slow	Vehicle type, Driver skills, Construction of highways
				[37]	2008 C	86.1	Sampling rate 20Hz	SVM, K-Nearest Neighbor, Karolinska Fatigue Scale, Time-domain Features, Frequency-domain features	N/A	Driving simulator	Non-intrusive, Robust	Not realistic, Complex implementation	Road characteristics, Environmental conditions, Personal driving performance
				[38]	2013 J	N/A	Sampling rate 70Hz	PCA, Psychomotor vigilance test	N/A	Ford Taurus in a fixed-base, high fidelity driving simulator Sensor of steering wheel angle	Cheap, Consumer friendly	Intrusive	Road surface, Weather conditions

J* Journal, C* Conference
CV* Computer Vision, DD* Drowsiness Detection, NVF* Non-Visual Features, N/A* Not Available, VF* Visual Features
HOSVD* Higher Order Singular Value Decomposition

PERCLOS (Percentage of Eye Closure) is a reliable and valid metric to determine the alertness level of the driver [49]–[52]. In literature, eye state analysis mostly exploits the PERCLOS value as drowsiness metric, which shows the percentage of time in a minute that the eyes are 80% closed [53], [54]. Generally, if the driver is tired, eye closure duration will increase and the

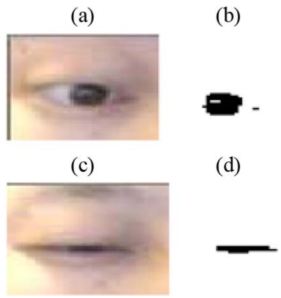

Fig. 1. (a) Normal eye region; (b) binary image after thresholding the image in (a); (c) blinked eye region; (d) binary image after thresholding the image in (c).

Fig. 2. Close and open eye template sample.

value of PERCLOS is higher than awake periods of a driver. To calculate PERCLOS, the eye region including the pupil area has to be extracted. On the other hand, eye blinking frequency changes and gets slower for sleepy drivers. However, there are some limitations in extracting those visual features. Two of them are improper lighting conditions and sunglasses. Some systems use IR (Infrared) cameras to overcome those problems [24], [49], [55], [56]. Also one disadvantage of PERCLOS is that sometimes a driver who is trying to stay awake could fall asleep with his/her open eyes [50]. On the other hand, mouth analysis and tracking the yawning frequency of a driver is an alternative way of detecting drowsy driver, especially when she/he wears sunglasses. For more robust and reliable driver inattention monitoring systems, researchers aim at analyzing facial expressions including both eye and mouth analysis.

In the following subsections, the mostly used techniques based on visual features are explained in detail. We mainly classified the techniques based on computer vision methods for detecting driver drowsiness as following:

- Eye State Analysis
- Eye Blinking Analysis
- Mouth and Yawning Analysis
- Facial Expression Analysis

1) Eye State Analysis: Eye state analysis, shown in Fig. 1, is the most common and simple technique for detecting driver drowsiness. The systems applying this technique focus on the states of eyes [23], [40], [41]. In such solutions, the system warns the driver by generating an alarm, if the driver closes his/her eye(s) for a particular time. Some available systems based on this technique use a database where both closed and open templates of eye are stored [42]. Fig. 2 shows a sample template of open and closed eyes.

In addition to non-adaptive systems, there are some adaptive solutions where the open and close eye templates of a related driver are exploited. Customized template matching technique on a frame-by-frame basis is used to detect the state of the two eyes [43].

On the other hand, eye state analysis is computationally intensive. In addition to that, there are some limitations, such as lighting conditions and sunglasses that affect the accuracy of the template matching technique. Another disadvantage of the template matching technique is that it would fail if the templates were distorted due to the image processing [43]. Because of the above reasons this technique is not sufficient enough to detect the driver's drowsiness. The overall accuracy rate of this technique is about 80% as given in Table I, [23].

2) Eye Blinking Analysis: As the eyes of drivers can provide observable information about fatigue level, many researches and studies exploit eye blinking frequency for drowsiness detection [44]–[49]. Those systems are based on monitoring the changes in the eye blinking duration. According to the study in [50], the eye blinking duration is the most reliable parameter for the detection of the drowsiness level. Since whenever a driver is tired or feels sleepy, his/her eye's blinking frequency changes and the eyelid closure duration starts involuntarily to prolong. To be more specific, when the driver is alert, his/her eye blinking frequency is low and his/her eyelid closure duration will be slower. However, when the driver is exhausted, his/her eye blinking frequency gets higher (more closed-eye images) and his/her eyelid closure duration will be shorter. The overall accuracy of this approach is around 90% [21]–[25]. The system diagram of eye blinking analysis is given in Fig. 3.

3) Mouth and Yawning Analysis: Most of the existing works, which exploit eye state features, suffer from the presence of sunglasses [57]. With regard to the driver's mouth state it is also possible to determine driver's sleepy level with yawning measurement [26], [27], [30], [58]–[60]. Yawning is an involuntary intake of breath through a wide-open mouth; usually triggered by fatigue or boredom. This technique is also one of the non-intrusive techniques for detecting driver drowsiness by applying computer vision. In this approach, as shown in Fig. 4, detecting drowsiness involves two main phases to analyze the changes in facial expressions properly that imply drowsiness. First, the driver's face is detected by using cascade classifiers and tracked in the series of frame shots taken by the camera. After locating the driver's face, the next step is to detect and track the location of the mouth. For mouth detection the researchers have used the face detection algorithm proposed by Paul Viola and Michael J. Jones [61]. Afterwards, yawning has been analyzed to determine the level of the drowsiness [59]. This is presumed to be modeled with a large vertical mouth opening and changes in the driver's mouth contour. Mouth opens wide and the distance between its counters gets larger. The normal and yawning states of the mouth are shown in Fig. 5 [29].

Yawning mouths have a higher chance of being detected, as they are bigger than a normal mouth. However, if a driver talks or sings while driving, it is sometimes not easy to distinguish these two activities from yawning, where both scenarios might lead to an open mouth and therefore a false positive might be

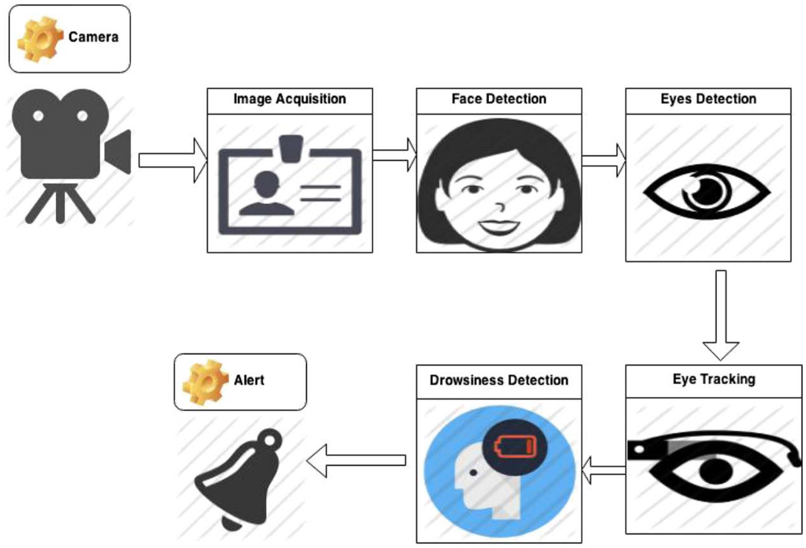

Fig. 3. The system diagram of eye blinking frequency analysis.

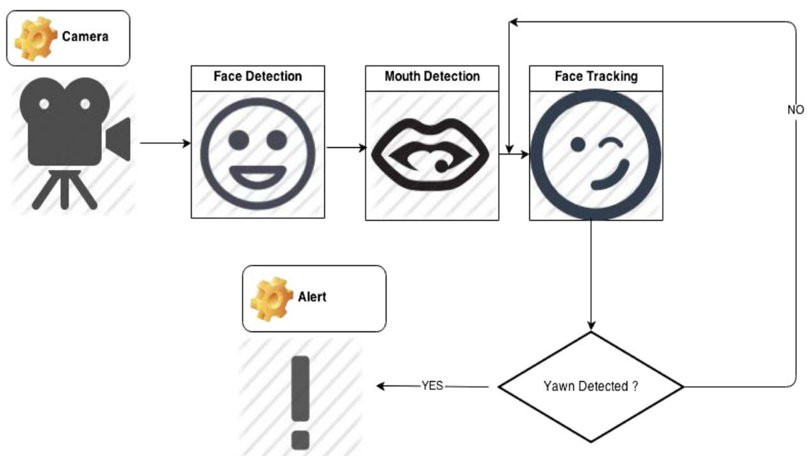

Fig. 4. The general system diagram of mouth and yawning analysis.

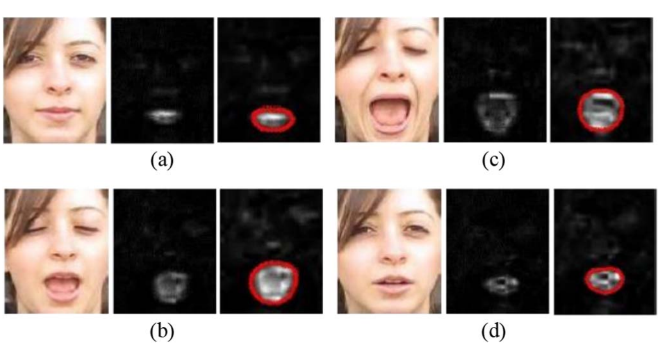

Fig. 5. (a) The normal state of the mouth. (b) The initial state of the yawning. (c) The mouth gets wider while yawning compared to speaking. (d) The mouth state after completing yawning.

detected. This is the main problem for the detection of yawning in such systems. Broadly, many researches detect yawning based on opening rate of mouth and the amount of changes in mouth contour area. According to the surveyed studies, given in Table I, the overall accuracy of this technique is about 80%.

4) Facial Expression Analysis: Contrary to exploit specific regions of face such as eye and mouth, this technique broadly analyzes more than one face region. ANN (Artificial Neural Network) is usually used for optimization of driver drowsiness detection [62]. In addition to that, it provides a different way to approach such a control problem, this technology is not difficult to apply and the results are usually quite surprising and pleasing. However, there are limited researches applied ANN to detect driver drowsiness [63]–[66].

Driver in fatigue exhibit certain visual behaviors that are easily observable from changes in facial features such as the eyes, head, and face. Visual behaviors that typically reflect a person's level of fatigue include eyelid movement, gaze, head movement, and facial expression. To make use of these visual cues, they made artificial neural network to detect drowsiness. Some proposed methods in [65], [66] use a neural network to scan an input window of pixels across the image, where each gray value in the input window serves as an input for the neural network. The neural network is then trained to give a high response when the input window is centered on the eye.

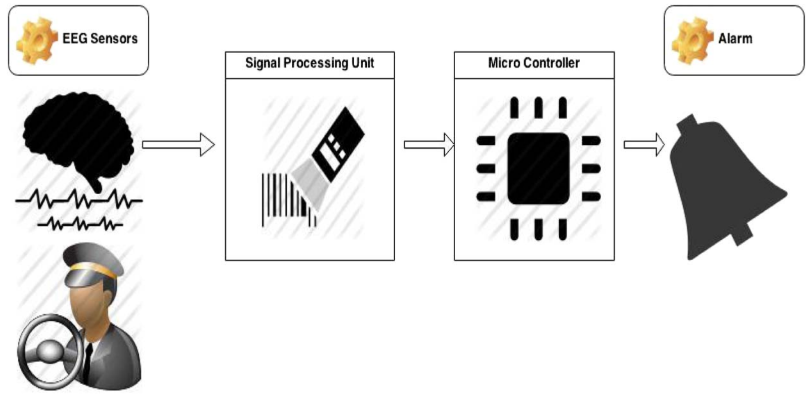

Fig. 6. The system diagram of driver physiological analysis using EEG sensors.

After scanning the entire image, the position with the highest response then reveals the center position of the eye in the image. For those systems the trained neural network easily predicted whether the eyes are open or close.

B. Techniques Based on Non-Visual Features

Non-visual features could be broadly categorized into two groups: driver-based and vehicle-based. Driver-based features usually refer to the brain activity and heart rate of a driver, whereas vehicle-based features include the pressure exerted on the brake, the fluctuation on the vehicle speed, the angle of the wheels, the steering wheel movement, etc. Under this section these techniques are briefly discussed in terms of detecting driver fatigue.

1) Driver Physiological Analysis: Fatigue and sleepiness directly affect the physiological indexes of a person. In [67], it was mentioned that the physiological indexes of state of drowsiness could be deviated from normal state. Hence, it is possible to detect driver's drowsiness by measuring physiological indexes, such as electroencephalogram (EEG), heart rate (ECG) and electrooculogram (EOG), of a person. The most promising and feasible method among these techniques is based on the measurement of driver's EEG, shown in Fig. 6.

EEG reflects the state of brain's activity. It is reported that when in the state of drowsiness, the activities of delta and theta waves are increased substantially, and the activity of alpha wave is increased slightly [34]. EEG is widely accepted as an indicator of the transition between the different sleep stages by researchers [68]. There are many researches that used EEG signals to detect driver drowsiness [33], [67]–[71]. Researchers conduct several tests in vehicle simulator [31], [33] and also in real vehicle [32], [34] and the results proved that the measurement of EEG is useful to detect driver's fatigue. To apply EEG signals in driver drowsiness detection, it is compulsory to wear electrode helmet by drivers while driving. This helmet has various electrode sensors on which obtain data from the brain as shown in Fig. 7 [69].

One critical issue in handling physiological signals is to eliminate noise and artifacts, which are inevitable in real-world driving conditions. To overcome this problem, some noise-reducing filters and various feature extraction techniques, such as Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT), are used. Then, the extracted features are classified using Support Vector Machine (SVM), Artificial Neural Networks (ANN), Linear Discriminate Analysis (LDA) [32]–[34], [69]–[71].

Fig. 7. An example setup of an EEG system.

The reliability and accuracy, given as over than 90% in [35], in detecting driver's drowsiness based on EEG signals are high when compared to visual features and other physiological indexes, such as ECG and EOG. However, researchers revealed that personal differences, such as gender and personality, influence EEG signals and could result in low accuracy rates.

On the other hand, an important limitation of EEG signal measurement is its intrusive nature. A possible solution to solve this limitation is to use wireless technologies such as Zigbee and Bluetooth for measuring physiological signals in a non-intrusive way by placing the electrodes on the steering wheel or in the driver's seat [32], [71]. But these kind of non-intrusive systems are less accurate than intrusive systems due to the lack of improper electrode contact.

2) Vehicle Parameters Analysis: Based on the analysis of vehicle movements, such as steering wheel movement, lane keeping, acceleration pedal movement and braking, etc., it is very likely to recognize the driver's state of drowsiness [38], [72]–[81]. These features are related to the vehicle type and can change according to drivers' driving habits, skills and experience. The two most commonly used vehicle movement features for detecting the level of driver drowsiness is the steering wheel

TABLE II
MOST REMARKABLE STUDIES FOR DETECTION OF DRIVER DISTRACTION

			Technique	Ref. No	Year J-C	Accuracy	Image/Video Parameters	Methods	Classifier(s) / Feature(s)	System Implementation	Advantages	Disadvantages	Limitations
DDD	VF	CV	Head Pose and Gaze Position Movements	[83]	2008 C	78	N/A	Thresholding, Smoothing	Haar-feature	WebCam, IR sensors	Less complex	Intrusive	Speed of the car, Driver's habit
				[84]	2008 J	97.3	Sampling rate 20Hz	K-Nearest Neighbors PCA, LDA	Haar-feature	UTDrive, Motion sensors, Controller Area Network (CAN)	Reliable, Feasible	Intrusive	Speed of the car, Road surface
				[85]	2010 C	N/A	25fps	Scale invariant feature transform	Cascade of boosted classifiers of the monocular, Haar-like	N/A	Non-intrusive, Robustness	Laboratory test, Only open eye detected	Illumination changes
				[86]	2012 C	75	10 Hz	Kalman filter	N/A	Toyota Hybrid Estima FaceLab	Real-time	Intrusive, Laboratory test	Speed of the car, Road surface, Driver's habit
				[87]	2014 J	94	N/A	Corner Detection Algorithm, CDF (Cumulative Distribution Function) Analysis, POSIT Algorithm, KLT (Kanade-Lucas-Tomasi) feature tracker, PMI (Pixel with The Minimum Intensity), MAE (Average Mean Absolute Error), Adabost and Viola Jones	Haar-features	Matlab, PC	Real-time, Reliable, Non-intrusive	Laboratory test, Single-modal system	Eyeglasses, Lack of objective indicators

J* Journal, C* Conference
CV* Computer Vision, DDD* Driver Distraction Detection, N/A* Not Available, VF* Visual Features

movement and the standard deviation of lateral/lane position [37], [73], [75].

Steering Wheel Movement (SWM) is measured using steering angle sensor mounted on the steering column. Besides, micro-corrections in steering are necessary for environmental factors such as small road bumps and crosswinds. Drivers tend to reduce the number of micro corrections in the steering wheel movements with increasing level of drowsiness [37], [73]. Some car companies such as Nissan and Renault are using SWM, but it works for limited cases [76]. SWM-based systems can function reliably only in particular environments and are too dependent on the geometric characteristics of the road and, to a lesser extent, on the kinetic characteristics of the vehicle [77], [78].

Vehicle instability is also one of the important signs for insecure driving. When the vehicle senses a loss of traction or a slip, it could immediately warn the driver. Moreover, the researchers design several control mechanisms for vehicle stability [126] in order to minimize car accidents. Sideslip angle estimation [128], an adaptive steering control system based on the Human Mechanical Impedance Properties (HIMPs) of the arms [127], and tire force distribution control mechanism for full drive-by-wire electric vehicles [129] are some recent studies in the literature.

There are other certain signs of driver inattention which can be interpreted from Standard Deviation of Lane/Lateral Position (SDLP) like leaving a designated lane and crossing into a lane of opposing traffic or going off the road. SDLP simply monitors the car's relative position within its lane with an externally attached camera. Special software is used to analyze the data acquired by the camera and computes the car's position relative to the road's middle lane [79], [80]. SDLP-based systems have some limitations that are caused by external factor, such as quality of road marking, weather, and lighting conditions.

Overall, there is a limited research available exploiting this technique. Vehicle movements for driver drowsiness measurements are easily affected by driving habit, driving skill, vehicle speed, vehicle characteristic, and road conditions. Therefore, a robust solution could not be formulated so far.

III. DRIVER DISTRACTION DETECTION TECHNIQUES

Distraction is anything that diverts the driver's attention from the primary tasks of navigating the vehicle and responding to critical events despite the presence of obstacles or other people. To put it another way, distraction refers to anything that takes your eyes off the road (visual distraction), your mind off the road (cognitive distraction), or your hands off the wheel (manual distraction) [82]. Driver distractions are the leading cause of most vehicle crashes throughout the world.

A good first step of detecting driver distraction or inattention is to monitor the driver head pose and gaze direction that infers quite reliable information about driver distraction. Head pose and gaze direction of driver can be measured by applying computer vision techniques properly. Different articles and studies were examined and several key factors including accuracy, advantages, disadvantages, limitations, methods, classifiers and system implementation for this technique are given in Table II.

Many researchers have used head pose and gaze direction to detect driver distraction. To determine whether the driver is looking straight ahead or not there is a forward warning system [88], [89]. It decides the driver distraction level using driver behavioral information. From a localized gradient histogram and support vector regressors (SVRs) it is also possible to determine driver awareness level by using head pose information extracted as it was reported in [90]–[92]. Head pose estimation provides a driver's field of view and current focus of attention. It is intrinsically linked to visual gaze direction. When the

Fig. 8. Sample set of gaze labels and head images. (a) Left-front. (b) Front. (c) Up. (d) Right-front. (e) Left-side. (f) Rear. (g) Down. (h) Right-side.

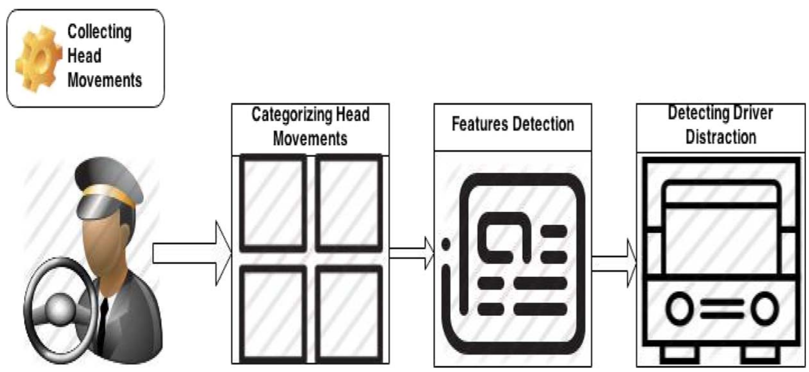

Fig. 9. The system diagram of head pose and gaze position analysis.

eyes are not visible, head pose is used to estimate the gaze direction. Head pose and gaze direction together provide the gaze information of a person [93].

The most common methods for the detection of head pose and gaze direction are shaped-based, appearance-based and hybrid methods [92]. According to comparisons of these methods in [92], the shape-based methods use a prior model of eye shape and surrounding structures, the appearance-based methods rely on models built directly on the appearance of the eye region. The appearance-based approach is conceptually related to template matching by constructing an image patch model and performing eye detection through model matching using a similarity measure. Hybrid methods take advantage of combination of shape and appearance approaches to exploit their respective benefits. Sample set of gaze labels and head images are shown in Fig. 8, [87]. Local features such as contours, eye corners, and reflections from the eye images are some important descriptors for these methods.

Also general gaze direction can be approximated by using only head orientation, which is computed by shape features with/without eye position, texture features or hybrid features consisting of both shape and texture features [94]. Overall head pose and gaze direction estimation is a good index that directly shows the current state of the driver distraction. According to the surveyed studies in Table II, the accuracy of this technique, shown in Fig. 9, is around 80%.

According to the study [58] it is also possible to detect driver distraction by monitoring arm and leg motions with some special sensors. However, in the literature there are not too many studies applying this technique.

IV. Enabling Mobile Technologies for Driver Monitoring

Previously conducted and developed systems [17] to detect driver drowsiness and sleepiness mostly come embedded into car systems which restrict their advantage due to associated high costs. On the other hand, considering today's mobile technologies it would speed up the proliferation of the available driver inattention monitoring systems by porting them into mobile platforms. Thus, people would start to exploit these non-intrusive affordable systems. We believe that all types of vehicles even the old ones could have its own driver safety solutions via mobile equipment, such as smartphones and wearable devices. The widespread usage of these low-cost and lightweight mobile devices composed of high speed processors, high-quality cameras and several sensors makes them a new alternative for safe driving. Especially, the built-in sensors allow to track driver and environment information, such as heart rate and arm movement of the driver, the sound inside the car etc. Thus, this obtained data would enable mobile applications to determine the fatigue and/or distraction level of a driver.

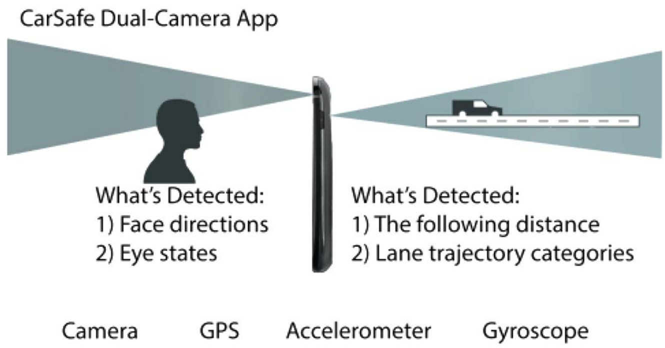

Fig. 10. CarSafe exploits dual-camera sensing to track both driver and road-based events [98].

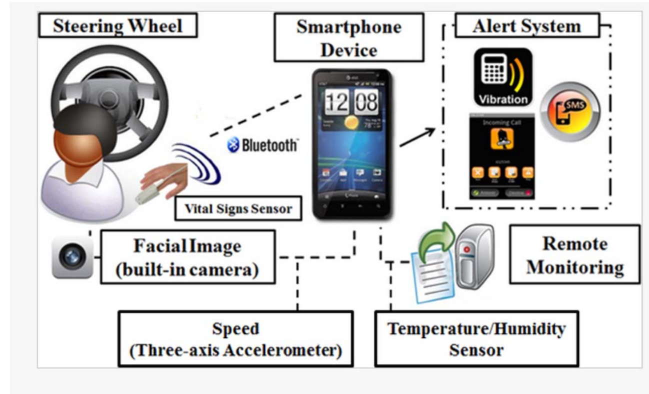

Fig. 11. The system design of smartphone solution [99].

A. Smartphone Solutions

Commercial solutions, such as iOnRoad [95] and Augmented Driving [96] focus on monitoring the following distance using the back camera of the smartphone. In addition to these commercial mobile applications, there are also some studies, which investigate the suitability of mobile technologies for safe driving. In [97], a mobile application for Android smartphones was developed that both detects driver drowsiness and sleepiness by applying image-processing techniques on video frames obtained via the front camera and alerts driver. Several tests have run at different lighting conditions and the overall accuracy is given as 85%. However, the system suffers from the same limitations, such as sunglasses and rapidly changing lighting conditions. In [98], a new driver safety app, CarSafe, was introduced which aims at detecting and warning drivers against dangerous driving conditions and behaviors. This application simply exploits computer vision and machine learning algorithms in order to monitor and detect whether the driver is tired or distracted using the front-facing camera, while at the same time tracking road conditions using the rear-facing camera. CarSafe focuses on five of the most commonly occurring dangerous driving events: drowsy driving, inattentive driving, tailgating, lane weaving/drifting and ignoring blind spots during lane changes as given in Fig. 10.

In [99], eye features, bio-signal variation, in-vehicle temperature and vehicle speed are used to monitor driver safety levels. This system was implemented as an Android application. It collects data from several sensors such as video, electrocardiography, photoplethysmogram, temperature, and three-axis accelerometer. If the driver's safety level is compromised, a fake incoming call alerts the driver. The overview of this system is given in Fig. 11. The proposed system consists of several modules. The smartphone receives data from ECG, PPG and humidity sensors that placed on the steering wheel. Driver facial image is captured via smartphones' front camera and vehicle speed is calculated with the help of built-in three-axis accelerometer [99].

B. Wearable Solutions

Mobile technological developments over the past few years have been growing faster than it was expected. From smartphones to the cloud computing, people are using the power of those technologies for being able to take control of their lives via a number of devices. Considering that wearable technologies found their way in our daily life with fashion and personal accessories, it would be smart to take advantage of their non-intrusive nature and to make effective use of them in driver drowsiness and/or inattention detection systems.

TABLE III
THE OVERVIEW OF SMART GLASS SENSORS

Sensors on Smart glasses	**Use**
3 axis gyroscope [100,103,105]	is used for measuring or maintaining orientation, based on the principle of preserving angular momentum
3-axis Accelerometer [100,102,103,105]	is a device that measures g-force.
3-axis-magnetometer [100,103]	is used to measure the direction of the magnetic field at a point in space.
Infrared proximity sensor [100,103]	is able to detect the presence of nearby objects without any physical contact.
Electrooculography [105]	is used to measure the cornea-retinal standing potential that exists between the front and the back of the human eye.
Pressure sensor [105]	is used to measure the blood pressure.

Probably one of the most noted wearable devices at the moment is Google Glass [100]. Google Glass has four sensors that could potentially be used for activity recognition: a camera, a microphone, an inertial measurement unit (IMU), and an infrared proximity sensor facing towards the user's eye that can be used for blink detection. In [101], the authors presented how the information about eye blinking frequency and head motion patterns gathered from Google Glass sensors can be used to categorize and analyze different types of high-level activities of the user. By taking the Google Glass as a prototype, there are other companies [102]–[105] which developed some smart glasses that effectively and aptly monitor a user's level of fatigue or drowsiness, and then acts accordingly to ensure safety and protection. As sensors play an important role to gather data for those smart glasses, we categorized mostly used sensors for the aforementioned products in Table III.

In addition to smart glasses, Fujitsu announced the launch of FUJITSU Vehicle ICT FEELythm [106], a new wearable sensor that detects when drivers are drowsy based on their pulse.

V. Driver Behavior Dissemination for Safe Driving

The available studies mostly focus on in-car solutions. However, vehicular communication enables the cars to disseminate data collected from car and driver. Thus, we believe that safe driving solutions will evolve in near future and more sophisticated systems will take place to warn drivers against other potentially threatening drivers. In this section, we first briefly introduce available in-car solutions, and then we will elaborate the studies based on car-to-car communication.

A. Commercial Driver Assistance Systems

An important amount of resources were used in the last decade to develop new technologies and features for driver inattention detection both by the automobile industry and some independent companies. This section provides brief information about those products.

1) Automobile Manufacturers: Increasing driving safety has been an active research area for many years and some auto companies, including Ford, Volkswagen, Nissan, Mercedes-Benz, Toyota and Volvo, have already used various technologies on their products to detect driver drowsiness and distraction. Some examples of these systems are given below according to their order of chronological appearance.

Lexus and Toyota: In 2006, firstly, Toyota has developed its Driver Monitoring System [10] for selected vehicles. This system includes a CCD (charge-couple device) camera, attached on the steering column to monitor driver behavior using eye tracking and head motion techniques. Also six near-IR sensors enable the system to work both day and night. Lexus introduced its solution as the Advanced Obstacle Detection System. It simply alerts the driver, if the driver turns his head away from the road during the vehicle movement and an obstacle is detected on the road.

Volvo: In 2007, Volvo presented a driver drowsiness detection system [11] by combining two safety features: Driver Alert Control System (DACS) and Lane Departure Warning (LDW). DACS monitors the car movements by checking whether the car is being driven in a controlled way or not. The system includes: (a) a camera, which is located between the windshield and the interior rear-view mirror to calculate the distance of the car to the road lane markings; (b) sensors, which register the car movements; (c) a control unit, which stores data to process. LDW system helps to prevent single road departure accidents and head collisions due to the distraction. However, it has some limitations because the system depends on the quality of road markings and good lighting conditions.

Mercedes-Benz: In 2009, Mercedes-Benz started to develop Attention Assist System for its series [12]. This system differs from the aforementioned systems, since it first learns the driver behavior by first monitoring the steering wheel movements and the steering speed. By creating a unique driver's profile it can easily determine the driver fatigue. The system works actively at speeds between 80 and 180 km/h.

Ford: In 2012, Ford presented its Driver Alert System [107]. The system monitors the vehicle's position in the lane and estimates the driver's alertness using a forward-looking camera.

Volkswagen: In 2012, Volkswagen introduced its Driver Fatigue Detection System [108]. This system automatically analyzes the driving characteristics and recommends the driver to take a break by measuring steering wheel movements.

2) Independent Systems: In addition to driver behavior analysis technologies introduced by car manufactures, there are also some aftermarket products available. The selected independent products are given as follows:

Eye Tracker: Fraunhofer Institute for Digital Media Technology in Germany developed this system [109], which utilizes two or more dashboard-mounted cameras to monitor drivers' eyes, and sounds an alarm if their eyes are off the road for long duration.

Anti-Sleep Pilot: This Danish designed device [110] is ked to complete a short test to create a personal risk profile. It also monitors the driving with a mounted kit on the car dashboard, and monitors the driver and driving conditions. By monitoring both driver and driving conditions, this system combines subjective methods with vehicle-based methods. To start using the Anti-Sleep Pilot, the driver needs to exploit of various built-in sensors.

Takata Safe Track: Takata Corporation developed this system [111] to monitor road ahead and warn the driver if the driver is out of lane or the driver's pattern indicates any irregular behavior.

Nap Zapper: As the name of the products indicates, this system [112] detects when the driver's head nods forward using electronic position sensors. This device is an inexpensive and quite simple device, attached over the driver's ear.

Vigo: Vigo [113] is the first wearable device to assess the driver alertness. It tracks the driver's eye movements and gives a gentle nudge when there are signs of the driver getting drowsy. It uses a built-in infrared sensor, an accelerometer to monitor the driver's level of alertness by tracking the driver's eye blinks and body movements. While wearing the device, Vigo records various parameters such as the driver blinks, its duration and eyelid closing/reopening times and transmits this data to the application for processing.

Intelligent Transportation Systems aim at providing safety on the roads. In this manner, VANET provides a wireless communication between vehicles and roadside units RSU [114], [116] to solve many driver and road-safety problems. The types of communication in VANET are presented in Fig. 12. Car-to-car communication enables departing vehicles to inform other vehicles on the road that they intend to depart the highway and arriving cars at intersections can send warning messages to other cars traversing that intersection. In literature, there are two main groups of applications using VANET capabilities for safe driving: accident prevention applications and collision avoidance applications.

Accident Prevention Applications: Roadside sensors can measure the road condition (e.g., slippery surface). They are placed at several positions on the surface and these sensors are

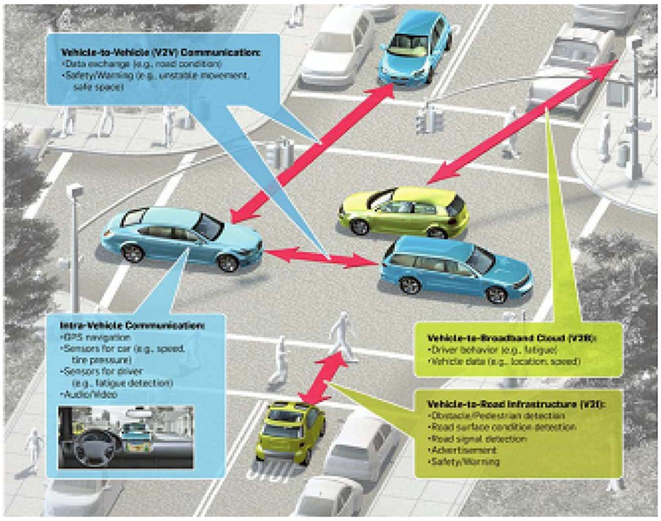

Fig. 12. Communication types in VANET [117].

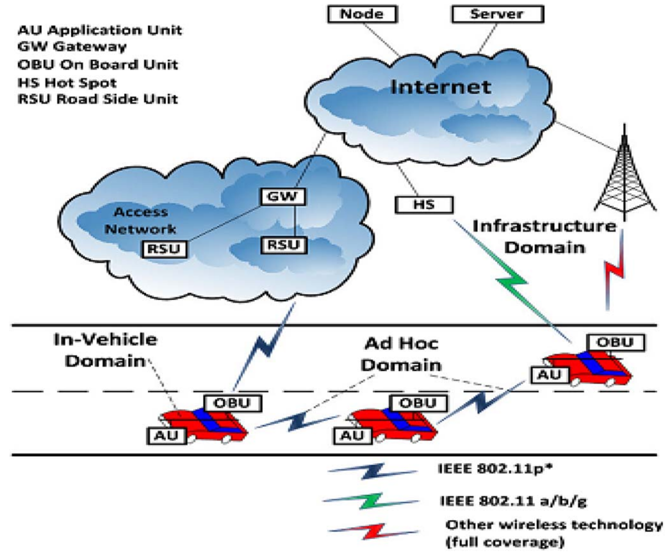

Fig. 13. Communication domain in VANET [118].

capable of collecting data, such as temperature, humidity, light, and detecting moving obstacles. In addition to that they are able to transfer the gathered information to an approaching vehicle. This vehicle generates a warning message and distributes it to all vehicles in a specific area, potentially using wireless multi-hop communication.

In addition to roadside sensors, with the help of sensors on smartphones carried by pedestrians, the consequences of driver distraction could be minimized. Furthermore, the driver, who is driving at wrong way/lane, could be warned by detection of drowsy drivers in cars approaching from opposite directions. Disseminating this information to other cars in real-time with the help of C2C communication channels could prevent accidents. And with the help of eye analysis of a driver, who is driving at opposite direction, the fatigue level of the driver could be determined and other drivers could be alerted about the dangerous drivers via VANET.

Collision Avoidance Applications: This type of applications aims at detecting the sudden deceleration while driving and warning the upcoming cars. If any accident or sudden deceleration occurs in a specific location, related vehicle broadcasts its location to its neighbor vehicle. And other vehicles try to transfer the message to the vehicles further behind them. During this process, a lot of drivers on the road behind can receive an alarm message before coming across the accident and may take timely precautions. Depending on the distance to the accident that occurred further along the road, vehicle can not only alert the driver but also automatically break the vehicle (e.g., emergency breaking) when the distance decreases under a certain limit. Also the data produced by cars at intersections or crossings can be exploited to reduce intersection collisions. Reporting accidents forward and backward to other cars on the same region can help to decrease the amount of collision related accidents on the highways.

Real-time analysis of driver behavior became quite popular research area with the emergence of ITS and VANET [119]. We believe that in near future, disseminating the information obtained from driver behavior detection systems via VANET would have a significant impact on reducing the number of vehicle accidents [116]. Thus, with the help of C2C communication not only the traditional car data will be transferred but also the information about the status of drivers will be shared while travelling. So far, VANET aims at delivering traditional data obtained from car sensors, such as speedometer, tire-pressure monitoring sensor, parking sensors etc. among the cars in order to inform the driver about the current condition of the related car. On the other hand, we believe that by using different type of sensors [120] driver-based information, such as drowsiness level, careless driver, vehicles travelling out of its lane, can be shared between vehicles by using VANET capabilities in order to prevent car accidents. Communication domains in VANET are shown in Fig. 13.

Most of the previous driver inattention monitoring systems is based on the information that is assembled from the driver behavior inside the car but it is also important to take advantage of the information that is gathered from cars in the neighborhood, which are coming from opposite direction or that follow same direction on the road. Detecting drowsy or careless drivers travelling in the vicinity would prevent fatal accidents and could save many lives. Thus, some researchers already focused on disseminating useful car and driver information with the help of vehicular communication. The study in [116] shows how to use sensors and VANET together to detect driver behavior as given in Fig. 14. There are many research studies exploiting VANET capabilities available in the literature [114]. For example, TrafficView [121] and StreetSmart [122] inform drivers through vehicular communication of the traffic conditions in their close proximity and further on the road to prevent driver related accidents.

VI. Future Directions and Conclusion

Comprehensive literature review showed us that each single technique has its own limitation, so it would be better to use the combination of several techniques. To achieve this goal,

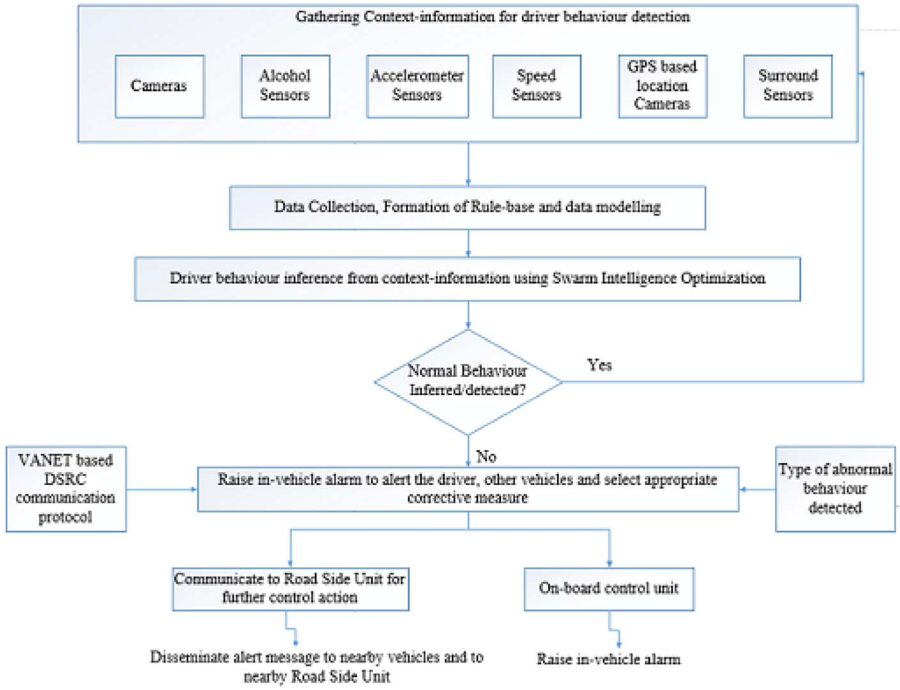

Fig. 14. Flowchart showing the mechanism of driver behavior detection system with VANET [116].

TABLE IV
A COMPARISON BETWEEN THE DRIVER FATIGUE AND DISTRACTION DETECTION TECHNIQUES

	Intrusive	Accuracy	Computational Cost	Robustness	Applicability	**Success Rate (%)**
EEG Signals	Yes	High	High	High	Low	88-98.2
Vehicle Movement	Yes	Low	High	Low	Medium	77-89.1
Head Movement	No	Medium	Low	Medium	Medium	75-97.5
Yawning Analysis	No	Medium	Low	Medium	Medium	80-91
Eye State Analysis	No	Medium	Low	High	High	80-98.4
Hybrid Solutions	Yes/No	High	High	High	High	N/A

recent studies [24], employ hybrid solutions in order to make the system more confident. Dong [124] presented a summary of some studies that use hybrid solutions for detecting the driver fatigue and distraction. These types of solutions score context relevant data. For fatigue detection, vehicle parameters, such as speed, acceleration, vehicle lane position, steering angle, braking, and facial features are evaluated together, whereas hybrid techniques for distraction detection combine eye movements, gaze variables, head orientation, hearth rate, CAN signals, driving data and road geometry. Moreover, these hybrid systems could be enhanced by taking into account personal characteristics such as gender, age and medical conditions. However, hybrid solutions take more processing time, since the number of evaluated features is increased.

A vast number of studies focus on the detection and/or monitoring of driver inattentions, whereas a small number of studies [10], [23], [28], [29], [34], [65], [79], [80], [83], [84] propose methods of alerting an inattentive driver. Common alerting mechanism techniques include vibration, sound, displaying a message and automatic car stop systems. We believe that future systems should include both in-car and inter-car alerting mechanisms. Our proposed concept of driver behavior dissemination via C2C communication is an enabling step towards inter-car alerting systems.

In conclusion, Table IV compares driver fatigue and distraction detection techniques using five criteria including intrusiveness, accuracy, computational cost, robustness, applicability and min-max success rates.

All the introduced methods are error-prone and thus they have some limitations regarding their use in real-life scenarios. Therefore, in our opinion, all the available commercial systems and non-commercial solutions should be regarded as assistance systems and they aim at helping drivers for detecting their moments of distraction and warning them. We believe that aggregation of the outputs of different sensors, such as camera, vehicle sensors, and body sensors would yield to more robust and reliable decision eventually. One of the possible scenarios of aggregation might be assigning weights to each sensor according to its robustness and resiliencies. On the other hand, hardware redundancy is another option to benefit from in order to tolerate hardware related sensing failures and thus to minimize fatal decisions. To this end, both visual and non-visual sensors such as accelerometer, gyroscope, proximity sensor and camera, could be deployed redundantly. However, this approach is bound with an extra budget, which is a trade-off for the deployment of these driver inattention monitoring systems. All in all, these systems are still progressing and they will eventually evolve into enactor systems.

In this study, we have reviewed and categorized the state-of-the-art techniques and next-generation solutions for detection of driver drowsiness and distraction. Besides, we introduce a new concept, driver behavior dissemination via C2C communication, which would be the next step éfor safe driving.

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