Recent Trends in Driver Safety Monitoring Systems: State of the Art and Challenges

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***Abstract*—Driving in busy highways and roads is becoming complex and challenging, as more cars are hitting the roads. Safe driving requires attentive drivers, quality perception of the environment, awareness of the situation, and critical decision making to react properly in emergency situations. This paper provides an overview on driver safety monitoring systems. We study various driver sources of inattention while providing a comprehensive taxonomy. Then, different safety systems that tackle driver inattention are reported. Furthermore, we present the new generation of driver monitoring systems within the context of Internet of Cars. Thus, we introduce the concept of integrated safety, where smart cars collect information from the driver, the car, the road, and, most importantly, the surrounding cars to build an efficient environment for the driver. We conclude by highlighting issues and emerging trends envisioned by the research community.**

***Index Terms*—Driver distraction, driver fatigue, driver states monitoring systems, integrated safety.**

I. Introduction

THE smart cities concept is becoming more and more of a reality, thanks to the spectacular integration of long-term evolution (LTE) networks (4G and 5G), wireless sensor networks, Clouds computing, Internet of things (IoT), and vehicular ad hoc networks (VANETs). One of the major objectives of smart cities is to improve quality of life by developing the "smart mobility" concept. VANETs are quickly becoming a cornerstone for enabling safety applications related to drivers, passengers, pedestrians, and traffic in the smart city. Indeed, these ad hoc networks, established over radio-equipped vehicles, are expected to contribute to road safety by providing pertinent information to drivers on potential dangers within their surroundings. This information can be related to any of the following: distracted driver, inattentive pedestrians, hazardous road conditions, animals, to name a few. As such, if a threat can be detected at an early stage, then appropriate maneuver(s) can be taken in a timely manner.

Nevertheless, more than half of the world's population now live in urban areas according to recent statistics of the United Nations. This increased urbanization results in continued growth in motorization, and, as such, cities suffer from acute traffic congestion and a dramatic increase in road casualties. Alarming statistics from the Association for Safe International Road Travel indicate that nearly 1.3 million people die in road crashes every year, with on average 3287 deaths a day [1]. At this rate, by 2030, road accident casualties will be the fifth leading cause of death. Moreover, more than 90% of road accidents are caused by human error. Indeed, a driver's behaviors can be affected by fatigue or drowsiness or by visual, cognitive, auditory, and manual distractions. Over the past decade, there has been significant research effort dedicated to the development of intelligent driver monitoring/assistance systems that enhance driver safety by monitoring the driver and on-road surroundings. Nevertheless, the in-vehicle environment is challenging, as there is a wide range of potential distractions to which drivers are exposed. These sources encompass secondary tasks (not related to the driving task) such as using a smartphone, navigation systems, and interacting with passengers or external distractions (i.e., crossing pedestrians, road construction, etc.). Whether fatigue or distraction, these factors leverage the driver driving capacity and affect his situation awareness. The purpose of the driver monitoring systems is to monitor the attention status of the driver and to take the countermeasure required to maintain driver safety. Despite that many automakers have already installed these systems in their connected cars, there is still a crucial need to develop more reliable and fast responding monitoring systems. Therefore, a distinction between the different types of distraction and fatigue is fundamental in order to develop an in-vehicle technology adapted to the detrimental effects induced by each source of drowsiness or distraction.

The remainder of this paper is organized as follows. We provide in Section II an overview on advanced assistance driving systems (ADAS). In Section III, we discuss the different sources of driver distraction since distracted/impaired driving is the main cause of road casualties. A comprehensive taxonomy of the different proposed frameworks, that tackle each kind of driver inattention, is also provided. The discussion on the new paradigm of

Manuscript received October 16, 2015; revised March 4, 2016 and September 2, 2016; accepted October 22, 2016. Date of publication November 22, 2016; date of current version June 16, 2017. The review of this paper was coordinated by F. Richard Yu.

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Digital Object Identifier 10.1109/TVT.2016.2631604

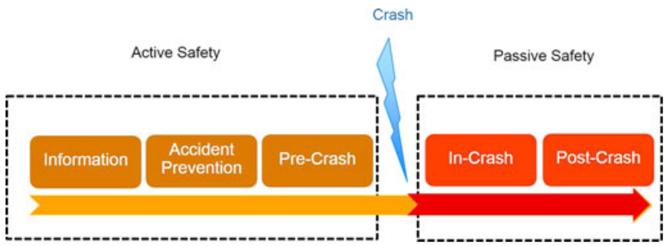

Fig. 1. Active and passive ADAS.

Internet of Cars and the concept of integrated safety as the new generation of driver states monitoring systems are provided in Section IV. Section V discusses future research directions and challenges of driver states monitoring systems.

II. Advanced Driving Assistance Systems (ADASs): An Overview

ADASs are designed to automate or adapt the car's electronic, mechatronic, and communication systems for safer travel journey. The purpose is to alert drivers to potential threats or mitigate collisions and help control the vehicle. ADASs are influencing the driving experience in more and more vehicles. Hence, developing reliable and cost-effective ADASs is a challenging task for cars designers. In this section, we provide a big picture on ADASs based on their ability to take a preemptive role in mitigating hazardous situations (active systems and passive systems) and system complexity (assisted, semiautomated, automated), as shown in Fig. 1.

A. Active ADASs

This type of ADAS acts preemptively to avoid an accident by taking control of the car [2]. It provides a response action before the crash to avoid an imminent accident or reduce its effects on the driver and the passengers. We can enumerate three subcategories.

1) *Informative systems:* The main objective of these systems is to provide drivers with additional information in a nonintrusive manner.
2) *Accident prevention:* These systems advise the driver to take corrective actions within a certain time margin (4–10 s). Typically, sensors (i.e., cameras, radar, laser, and ultrasonic) monitor the environment (i.e., road, surrounding vehicles, and pedestrians) and warn the driver of any accident hazards before intervening to mitigate the crash.
3) *Precrash:* These systems intervene in a crash-imminent situation. The duration of the precrash phase is computed from the early detection of the accident to the occurrence of the actual crash. The technologies used here aim at reducing crash energy.

B. Passive ADAS Systems

These systems refer to the safety-embedded technologies in the car that mainly target occupant protection and injuries reduction during a crash. These passive systems play a crucial role when the active safety measures fail in preventing an imminent accident. The first hour after the crash is called the golden hour where the mortality incidence is very high (about 75% of all deaths) [3]. This death rate can be substantially reduced through an efficient intervention of passive safety systems in both in-crash and postcrash stages. This is described next:

1) *In-crash:* The in-crash phase begins at the contact with the colliding object and ends when the vehicle is at rest at the crash scene.
2) *Postcrash:* The postcrash phase occurs immediately after impact. The role of an ADAS in this phase is to provide most appropriate emergency care and facilitate the rescue of the involved victims.

Fig. 2 illustrates ADAS classification based on the response time action and the degree of automation. This classification is based on the study carried out by Eskandarian [2].

In the remainder of this paper, we focus on driver state monitoring systems, as they constitute a major category of active of ADAS.

III. Driver Status Monitoring Systems: Overview and Taxonomy

As discussed in the previous section, ADASs promise to enhance vehicle safety by assisting the driver in complex traffic situations by avoiding taking the wrong decisions and especially reducing sources of driver distraction and inattention. Driver distraction causes are diverse and increase subsequently the risk during driving. Direct attention is crucial not only to perceive cues but to take the appropriate decisions in the high dynamic driving environment.

A. Driver Inattention; Definition and Frameworks

Driver inattention can be defined as "insufficient, or no attention, to activities critical for safe driving" [4] and can be classified into several subcategories, as reported in [4].

1) Driver restricted attention (DRA)—This inattention is attributed to insufficient or lack of attention due to the biological factors, e.g., fatigue. These factors prevent the driver from performing safe driving activities.
2) Driver misprioritized attention—This inattention is caused by the driver inability to efficiently distribute attention to several driving activities. This type of inattention is commonly experienced by young novice drivers.
3) Driver neglected attention—The absence of attention to critical driving activities caused by the driver's attention neglect of activities that are critical for safe driving.
4) Driver cursory attention—The inattention occurs because the driver is providing cursory attention to activities critical for safe driving.
5) Driver diverted attention—The deviation of attention from the main critical driving activities due to a competing activity. This kind of inattention is commonly called "driver distraction."

In [5], another set of definitions of driver inattention are provided.

1) Secondary task distraction—Driver activities that distract driver's focus from the primary driving activities due to activities not related to driving.

Increasing complexity

Temporal progression

ADAS / Features		Function	Assisted	Semi-automated	Highly automated
Active Safety	Information	-Provide usuful information that can affect the driver's decision and actions (road conditions, stopped traffic, etc)	- Park assist - Traffic Sign Recognition	- Intelligent park assist	
	Accident Prevention	- Warn a potentiel hazard and propose eventually a recommandation signal of corrective action	- Lane departure warning - Lane keeping assist -Collision warning	- ACC - Emergency Brake assist - Emergency steer assist - Electronic stability program	-Active safety system Collision Mitigation (CM)/Collision Avoidance (CA)
	Pre-Crash	- Mitigates hazards actively, without direct input from the driver.		- Emergency steer assist	- Collision mitigation
Passive Safety	In-Crash Action	- Reacts immedialty to protect occupants and mitigate damages.			- Pedestrian protection Airbag -Occupant Interaction Airbag
	Post-Crash Action	- Inform automatically emergency services when and where a crash has occurred - Data recording			-eCall - On-Star

Fig. 2. Taxonomy of ADAS.

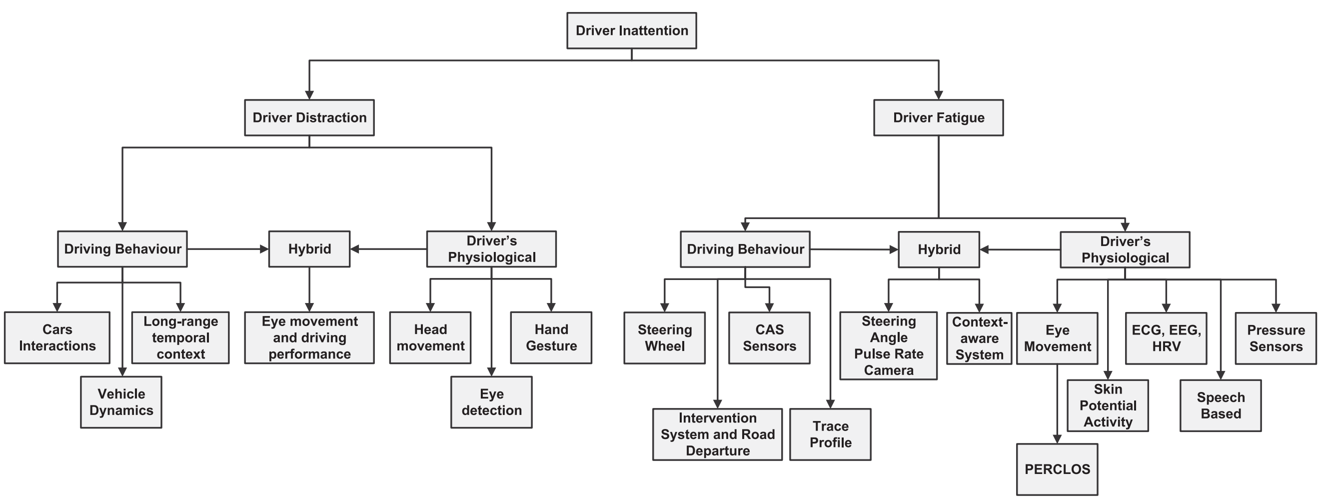

Fig. 3. Taxonomy of driver inattention sources.

2) Driving-related inattention—Driver activities that distract driver's focus from the primary driving activities due to driving-related activities.
3) Drowsiness—Driver biological behavior that prevents driver from performing critical activities for safe driving, e.g., eye closures, repeated yawning, and other behavior that are categorized as drowsiness.
4) Nonspecific eye glance away from the forward roadway [5].

Based on the definitions provided in [4] and [5], we conclude that there are similarities between the two set of definitions: DDA-NDR is similar to secondary task distraction, while DRA is similar to drowsiness. Furthermore, the term driver distraction will be used to replace DDA-NDR and secondary task distraction, while the term driver fatigue will be used to replace DRA and drowsiness. A taxonomy of driver inattention sources are depicted in Fig. 3.

B. Driver Distraction: Definition and Frameworks

Several definitions for driver distraction, considered as a specific form of inattention, have been established in the literature. The most accepted definition of driver distraction is "a diversion of attention away from activities critical for safe driving toward a competing activity" [6]. The term "competing activity" is related to interactions between the driver and passengers, thoughts, in-vehicle technology, food, and noncritical driving activities [7]. Although distraction may take various forms, most of them can be grouped into four categories [8].

1) Visual distraction—distraction that demands the driver to switch the view away from the roadway, e.g., looking at a traffic sign.
2) Auditory distraction—distraction that demands the driver's auditory focus, e.g., responding to conversation with other passengers.

3) Biomechanical distraction—distraction that requires the driver to take the hands away from the steering wheel, e.g., using cellphone.
4) Cognitive distraction—distraction that requires cognitive workload other than the primary driving task, e.g., daydreaming.

In addition, in terms of complexity, distraction may also be partitioned into three levels [5]: simple, moderate, and complex. However, crash risk due to distracted driving is affected not only by the types of distraction or the complexity levels but also by the frequency and duration of the distracting actions [9]. In other words, frequent simple distractions may have similar effect as complex distractions. Subsequently, certain distraction activities can be categorized into two or more distraction types. For example, text messaging can be considered as visual, manual, and cognitive distraction since the activity involves the driver's vision, hands, and mind.

Most of the existing systems that detect driver distraction are built based on three measures: driving behavior, driver's physiological state, and hybrid. We present in the next section a literature review for driver distraction detection systems.

1) Driving Behavior Measures: Although the signals of driving performance measures are readily available, they have been rarely used in research literature. Most of the work on driver distraction detection has involved combinations of driving behavior and driver's physiological measures to have better detection accuracy. In the following, we summarize main body of work on driver distraction detection based solely on driving behavior measures.

1) *Vehicle dynamics:* The use of in-vehicle information systems and partially autonomous driving assistance systems may cause distracted driving. Fabio *et al.* [10] introduce a nonintrusive visual distraction detection system based on vehicle dynamics data. The authors classify distracted driving using machine learning techniques, namely artificial neural network (ANN) and support vector machine (SVM). The results show that the accuracy of the classifiers is not satisfactory. According to the authors, this is due to the use of an intersubject analysis, while the distraction response is highly subjective. The extension presented in [11] uses an intrasubject analysis on a nonintrusive and real-time visual distraction classification based on vehicle dynamics data. Subsequently, the accuracy of the extended method is significantly higher than that of the previous work.
2) *Long-range temporal context of driving:* A novel technique is developed in [12] to complement the existing lane-keeping assistance systems for vehicles. The long-range temporal context of driving and head tracking data are modeled using long short-term memory (LSTM) recurrent neural networks, which enables a reliable subject independent driving inattention detection. It is claimed in [12] that the proposed LSTM framework outperforms standard classification approaches such as SVM.

2) Driver's Physiological Measures: Cognitively demanding tasks affect driver's behavior, such as eye glance pattern, forward view angle, head movement, and other physiological measures. To recognize these physiological measures effectively, a video camera is used to capture driver behavior. In the following, we present several studies on vision-based driver distraction detection systems.

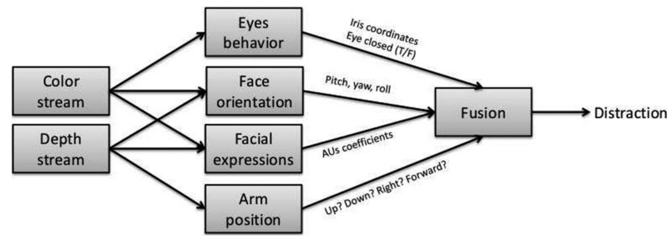

Fig. 4. Context-aware driver status assessment systems [18].

1) *Head movement:* The development of distracted driving detection systems based on Microsoft Kinect motion sensing hardware is proposed in [13]. The Kinect is utilized to track head and skeletal movement so that the driver's gesture can be identified. The tracking algorithm is based on the relative distances between spatial locations of the skeletal joins, and the rotation of the head.
2) *Eye status detection:* In [14], a vision-based driver monitoring system is introduced. The system uses an eye-detection algorithm, which is a combination of adaptive boosting, adaptive template matching, and blob detection. To increase the detection accuracy, a validation is applied using SVM. Another vision-based distraction detection system is developed in [15]. This work proposes the development of a real-time eye status detection system, which uses optimal Haar-training parameters to create a nested cascade of classifiers.
3) *Mouth movement:* A study conducted in [16] employs driver's eye and mouth movement data, which are collected using FaceLab Seeing Machine cameras, to detect cognitive distraction. The results show that combining driver's eyes and mouth movements enhances detection of cognitive distraction.
4) *Facial expression and arm position:* In this approach, several cues related to fatigued and distracted driving are observed, i.e., arm position, eye closure, eye gaze, facial expressions, and orientation. Ragab *et al.* [17] gather data using the system designed by authors of [18]. In this system, Kinect and infrared cameras are attached to a car simulator. The different submodules for assessing driver inattention are depicted in Fig. 4.

   Ragab *et al.* compare the performance of several classifiers, i.e., random forest, AdaBoost, hidden Markov models, SVM, conditional random field, and neural network, for distracted driving detection.

3) Hybrid Measures: Intuitively, hybrid measures, i.e., the combination of driving behavior and driver's physiological measures, may enhance the quality of the driving distraction detection. Hirayama *et al.* [19] introduce a cognitive distraction detection system based on eye gaze and peripheral vehicle behavior. It is concluded that the driver's state affected the temporal relationship between the driver's gaze and the peripheral vehicle behavior. The system employs a Bayesian framework for the detection, which produces higher accuracy than road center method does. In more recent work, the integration of dynamic

TABLE I
COMPARISON OF DISTRACTION DETECTION APPROACHES

Driver Distraction	Dataset	Pros	Cons
[10]	simulation	- nonintrusive - multimodal information	- delay of distraction detection - lack of generalization due to the limited datasets
[11]	simulation	- model personalization - nonintrusive - multimodal information	- delay of distraction detection - lack of generalization due to the limited datasets
[12]	real-world	- high-accuracy results - nonintrusive - multi-modal information	- noncomplex driving distraction detection - lack of generalization due to the limited datasets
[13]	simulation	- capability to detect specific driving distractions - nonintrusive - multimodal information	- limited behavioral scenarios - lack of generalization due to the limited datasets
[14]	real-world	- nonintrusive - multimodal information	- lack of generalization due to the limited dataset
[15]	simulation	- large datasets	- unimodal information
[16]	simulation	- multimodal information	- lack of generalization due to the limited datasets
[17], [18]	simulation	- capability to detect specific driving distractions - nonintrusive - multimodal information	- lack of generalization due to the limited datasets
[19]	real-world	- multimodal information	- lack of generalization due to the limited datasets - intrusive
[20]	simulation	- multimodal information - nonintrusive - efficient computation	- lack of generalization due to the limited datasets
[21]	simulation	- multimodal information capability to detect specific driving distractions	- lack of generalization due to the limited datasets - partially intrusive

Bayesian network (DBN) and supervised clustering to detect cognitive distraction based on eye movement and driving performance, i.e., steering wheel and lane positions, is proposed in [20]. The data used to train the algorithms are obtained from a simulator, where the driver performed driving actions with and without auditory distraction. The algorithms are compared to the previously developed DBN and SVM algorithms. Although the results show that the proposed algorithms achieve comparable performance to the previous work, the training and prediction time are improved drastically. Recently, Craye *et al.* [21] proposed a holistic approach for fatigue and distraction detection. Captured features are grouped into three modules: vision, audio, and other signals (steering wheel, pedal position, and heart rate) modules. Each module operates independently and can be enabled or disabled. Then, each module provides its own estimation of driver fatigue/distraction. The final estimation is done by the fusion of each estimation provided by each module using Bayesian networks.

To highlight the performances and capabilities of the listed approaches, we present a qualitative comparison; the quantitative one, in terms of accuracy, reliability, and other quantitative measures, is not suitable since each approach uses different datasets and experimental settings.

Table I summarizes the qualitative performances and capabilities of approaches proposed by some researchers in terms of pros and cons. As can be seen from the table, the majority of the approaches use simulation datasets. These datasets refer to datasets that are generated from driving simulation scenarios, while real-world datasets refer to datasets that are generated from real driving environment, i.e., real cars and real traffics. Almost all of the approaches are lack of generalization due to the limited number of participants in the data collection processes. Driver distraction detection systems are highly subject dependent. Furthermore, a large number of participants are required to achieve sufficient generalization.

C. Driver Fatigue: Definition and Frameworks

Another subset of driver inattention is driver fatigue. It is defined in [22] as the result of symptoms (impaired performance) and their factors (long awake period). In [23], fatigue is categorized into four groups: local physical, general physical, central nervous, and mental fatigue.

The central nervous fatigue is an important type of fatigue which is connected to "the level of brain stimulation and the structures that regulate it" [23]. In terms of sleepiness level, the "central nervous" fatigue is categorized into four levels: completely awake, moderate sleepiness, severe sleepiness, and sleep. These levels of sleepiness are a combination of the amount of activity and the brain's waking capacity [23], which are affected by several factors. These factors will modify the sleepiness threshold. To detect whether a driver is fatigued or not, the following symptoms have to be recognized [24]: repeated yawning; confusion and thinking seems foggy; feeling depressed and irritable; slower reaction and responses; daydreaming; difficulty keeping eyes open; lazy steering; difficulty maintaining concentration; swaying of head or body from nodding off; vehicle wandering from the road or into another lane; and nodding off at the wheel.

There are three main approaches to recognize fatigue symptoms: driving behavior, driver's physiological, and hybrid measures. The following subsection summarizes works that have developed in fatigued driving detection system.

1) Driving Behavior Measures: Studies carried out include the assessment of 1) steering wheel motion, 2) vehicle state information, 3) road departure detection, and 4) other accessible sensors. This section presents an overview of related work on fatigued driving detection based on driving behavior measures.

1) *Steering motion:* The estimation of fatigued driving based on steering motion is presented in [25]. The chaos detection in the motion of the steering wheel is based on chaos theory. The data from the steering wheel are preprocessed by fast Fourier transform and wavelet transform. The fatigued driving is then determined based on the attractor trajectory. In [26], a fatigued driving monitoring system based on a pattern of slow drifting and fast corrective counter steering is proposed. The extracted features are learned using some machine learning methods, such as SVM, K-nearest neighbor, etc. Then, the classification results are combined using an ensemble learning technique to predict accurate driver's states. Another work employing steering wheel data to detect fatigued driving is proposed in [27]. In this work, data are collected from a driving simulator that are driven by 12 participants. Then, data are classified into drowsy and nondrowsy driving using ANN.
2) *Road departure:* In [28], an intervention system and a road departure warning is investigated. To develop the fatigue recognition model, the authors proposed a system identification technique using lateral position as the input and steering wheel as the output. The simulation results show that the adopted model has acceptable accurate identification.
3) *Vehicle state:* A study of fatigued driving detection based on the vehicle state information is investigated in [29]. The vehicle states such as steering angle and trace profile are analyzed using the localized energy method. The experiment shows that the driver's states have effect to the vehicle behavior, which can be used to determine the fatigued driving state.
4) *Collision avoidance system (CAS) sensors:* A driver inattention monitoring system using CAS sensors are developed by Torkkola *et al.* [30]. The data obtained from the sensors are then classified using machine learning techniques. This system is able to produce high classification accuracy without adding cost of additional sensors.

2) Driver's Physiological Measures: Fatigue can be effectively measured by humans physiological condition. We highlight the following physiological measures.

1) *Eye and face movement:* Lee and Chung [31] develop an Android-based system that combines eye movement and biosignal data to monitor driver drowsiness. Another smartphone-based driver fatigue detection technique is developed in [32]. In this work, both the driver's eye and face are tracked. A novel fatigued driving monitoring system based on the multivariate hierarchical Bayesian network is proposed in [33] to alleviate the high error rates of image-based fatigue monitoring systems. The proposed system consists of four modules: face region detection, eyelid closure judging, head positioning, and fatigue analyzing. In [34], the authors resort to an infrared camera-based driver fatigue surveillance system. The goal of using the infrared camera is to extract more easily human's pupil images. These images are then classified using a backpropagation neural network. Khan and Mansoor [35] design a cross-correlation function-based classifier to classify eyelid movement. When the eye closure is detected for more than a specified threshold time, an alert signal is then generated.
2) *Speech:* A study by Li *et al.* [36] proposes a speech-based fatigued driving monitoring system. The detection algorithm is built using nonlinear speech processing techniques combined with fuzzy SVM. In addition to the classical SVM method, a fuzzy clustering method is used to compensate the noise and outliers. The experimental results have shown the feasibility and effectiveness of the proposed method to recognize fatigue.
3) *PERcent of Eye CLOSure (PERCLOS):* PERCLOS is a video-image-based method to track eye closure. It is calculated as the total time that the driver's eyelids are closed 80% or more [37]. In [38], PERCLOS is used as the input of the AdaBoost classifier. The results showed that the method is able to identify the state of the eye under natural lighting conditions. An eye detection method based on active appearance model (AAM) is introduced in [39]. The AAM model is used to detect the position of the head and the location of the eyes. Then, the PERCLOS of the detected eyes is measured to justify whether the driver is drowsy or not. Since PERCLOS has its limitations, an infrared video-based fatigued driving detection system is developed in [40]. The system merged the characteristics from eyes and mouth to improve the detection accuracy.
4) *Pressure sensors:* Another method to detect fatigued driving is based on pressure sensors [41]. The variation in steering grip force can be used to observe driver's state, e.g., fatigue and loosing alertness. The force data are obtained using two resistive force sensors positioned on the steering wheel. The log-likelihood ratio is used to determine the alertness of the driver. In [42], a multisensory platform for the driver inattention detection system is introduced. The authors implement a multiview classification method based on particle swarm optimization to fuse pressure sensors and video camera.
5) *Skin:* In [43], the authors propose an approach to detect fatigued driving based on photoplethysmograpy signals. These signals generate the pulse rate variability signal, which can be used to measure the autonomous nervous system activity. The authors of [44] match the performance of the response during monotonous tasks with skin potential activity to identify the drowsy driving.
6) *Biological signals:* These signals are mainly:
    a) the electrical activity along the scalp (EEG);
    b) the electrical activity of the heart (ECG);
    c) electrical activity associated with eye movements (EOG);
    d) the electrical activity produced by skeletal muscles (EMG).

    Jung *et al.* [45] use a new ECG sensor to detect driver's health condition. The sensor is embedded on the steering wheel and is used to measure the driver's heart rate through the driver's palm (see Fig. 5). Data from sensors are then

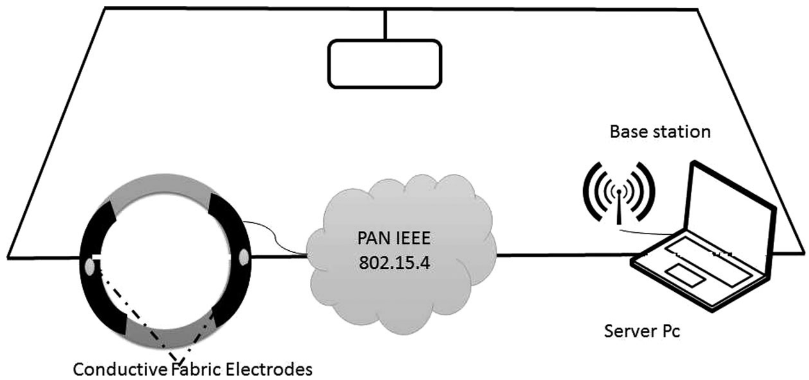

Fig. 5. ECG sensors embedded on a steering wheel to detect driver's health [45].

used to determine driver's condition such as normal and fatigue.

A real-time driving fatigue identification based on EEG, EMG, and EOG is designed by Zhang *et al.* [46]. The measurements from sensors are used to determine fatigue based on various entropy and complexity measures. Some entropies (wavelet entropy, sample entropy, and peak-to-peak value of ApEn) are used to recognize driver states (normal, mild fatigue, mood swing, and excessive fatigue states). Besides, a system that combines EEG and visual activity to detect fatigued driving is designed in [47]. Diagnostic techniques and fuzzy logic are used to detect drowsiness based on the EEG brain activity and EOG blinking data. The results of both data classification are then combined using cascading decision rules to determine the scale of drowsiness. Heart rate variability (HRV) is one of the physiological measure that can be used to detect fatigued driving. However, the accuracy of the detection using HRV as a stationary signal is questionable. Therefore, Li and Chung [48] resort to wavelet transform of HRV data. This transformation provides richer data and ensures accurate classification of drowsy driving.

3) Hybrid Measures: Combining driving behavior and driver's physiological measures ensure increasing of the detection confidence, which results in more reliable systems. The fusion of driver physiological and driving performance measures is introduced in [49]. The data generated from several sensors are fused using an ANN and a stochastic optimization method. To validate the results, the ground truth is generated based on a supervised Karolinska sleepiness scale. Another fatigued driving monitoring system based on hybrid measures is developed in [50]. The system uses depth camera, pulse rate, and steering angle sensors to detect whether the driver is in fatigue driving condition or not. The data obtained from the sensor then are fused and classified using multilayer ANN. The system has successfully classified three levels of drowsiness with high accuracy. Al-Sultan *et al.* [51] introduce a driver state detection system based on a context-aware system in VANET. The context-aware architecture consisted of five layers, which have the ability to collect contextual information about the driving environment, to reason about certain and uncertain contextual information and to react to the available flow of information. The inference mechanism is performed in real time by a set of DBNs.

Similar to the comparison of driving distractions detection systems, fatigue detections approaches are compared based on the cons and pros provided by the listed approaches. Table II shows a summary of the qualitative performances and capabilities of approaches proposed by some researchers.

IV. Driver Monitoring Systems in Internet of Cars: Recent Trends

Frameworks mentioned in previous sections focus only on the driver behavior and its interactions with in-car sensors. This limited observation through driver's car cannot handle efficiently road crashes in a smart city. The driver is an integrated part of a chain that is larger than its vehicle. This chain includes humans, vehicles, and environment (roads, infrastructure, traffic signals, mobile Internet, and Clouds). This global framework represents the Internet of Cars, and it provides drivers not only with in-car reasoning and decision capabilities but with external environment capabilities as well. In the next section, we give an overview Internet of Cars and highlight its abilities in providing vehicles with a deep understanding of the dynamic entities within their environments, hence impacting drivers actions. Integrated safety, the new wave of driver states monitoring systems shaped by Internet of Cars, is also highlighted.

A. Internet of Cars: An Overview

Conventional VANETs consider each participating car (itself comprising a large number of sensors) as a wireless mobile node that can connect one another hence, creating a wide range network. Recent technological advances have brought car designers to low-cost and high-performance sensors such as radar (forward looking obstacle detection), on-board camera (pedestrian detection, lane keeping, driver monitoring), infrared (night vision), ultrasonic (automated parking), and light detection and ranging (LiDAR) sensors. These sensors continuously capture information from the car, the driver, and the road. This information is then fed to the driver, to the embedded systems within the car, the highway infrastructure, and to the cloud. Thus, the car becomes a smart "thing" that can talk to other cars, people, and roads through the Internet and other communications protocols.

TABLE II
COMPARISON OF FATIGUE DETECTION APPROACHES

Driver Fatigue	Dataset	Pros	Cons
[25], [28], [29]	simulation	- nonintrusive	- unimodal information - lack of generalization due to the limited datasets
[30]	simulation	- nonintrusive - multimodal information	- lack of generalization due to the limited datasets
[31]	real-world	- multimodal information	- lack of generalization due to the limited datasets - intrusive
[36]	simulation	- large datasets	- unimodal information
[38]	simulation	- multimodal information	- lack of generalization due to the limited datasets - intrusive
[42]	simulation	- capability to detect specific both driving distractions and fatigue - nonintrusive - multimodal information	- lack of generalization due to the limited datasets - nonspecific fatigue detection
[43]	simulation	- nonintrusive	- lack of generalization due to the limited datasets - nonrealistic driving environment - unimodal information
[45]	real-world	- nonintrusive	- lack of generalization due to the limited datasets - unimodal information
[50]	simulation	- multimodal information - nonintrusive - multilevel drowsiness detection	- lack of generalization due to the limited datasets

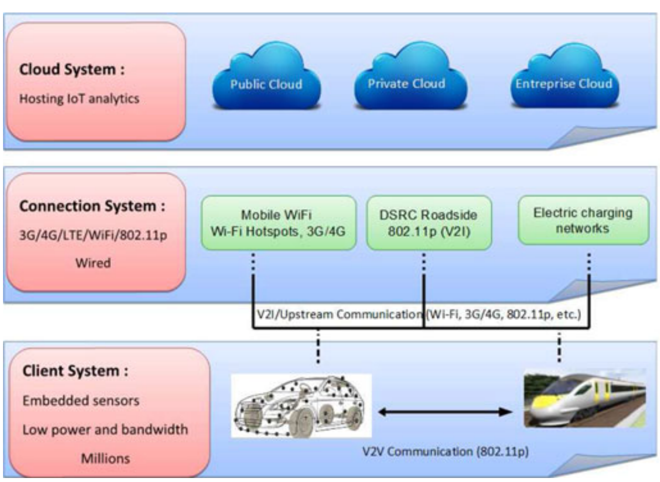

Fig. 6. Internet of Cars: Different layers.

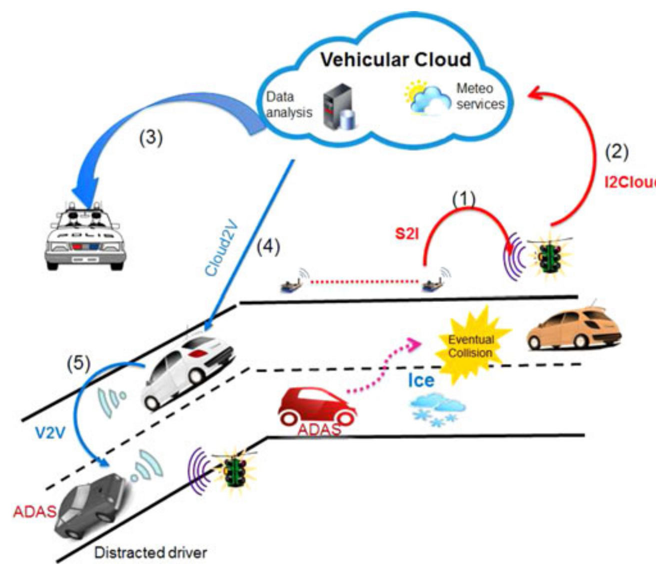

Fig. 7. Illustrative scenario of Integrated Safety in Internet of Cars.

As such, connected cars are evolving toward connected things that can discover themselves autonomously and connect and interact with surrounding cars to ensure safer driving. Hence, the IoT is paving the way for the evolution of VANETs into the Internet of Cars. Smart cars will constitute a key component of connected "things." Hence, cars are evolving from mobile nodes that can disseminate information to intelligent agents with powerful sensing, reasoning, and decision capabilities [52].

The Internet of Cars system is a three-level "client–connection–cloud" system [53], as depicted in Fig. 6.

1) The client system: It is the set of sensors inside the intelligent car. Those sensors gather data and detect driving conditions and the environment. It also features the different intravehicle, intervehicle, and vehicle-network communication.
2) Connection system: This layer deals with the different kinds of wireless communications (V2V, V2R, V2H, V2I, etc.) in order to ensure connectivity and the roaming of existing networks (VANETs, UMTS, LTE, Zigbee, etc.).
3) Vehicular Cloud system: The cloud offers network access to mobile cars. It was first introduced by Gerla [54]. The cloud is constructed by collaborations among cloud vehicles and road side units (RSUs) hence enabling the fusion and sharing of databases. Recently, Bosch has developed a new cloud-based driver warning system that alerts drivers within seconds if they are going in the wrong direction [55]. If the actual vehicle and lane direction do not match, the system issues immediately an alert for the current vehicle and oncoming vehicles traveling in the opposite direction.

Thus, Internet of Cars generates new opportunities for safe driving and provides an excellent platform for assisted driving systems. Let us consider the scenario depicted in Fig. 7. The

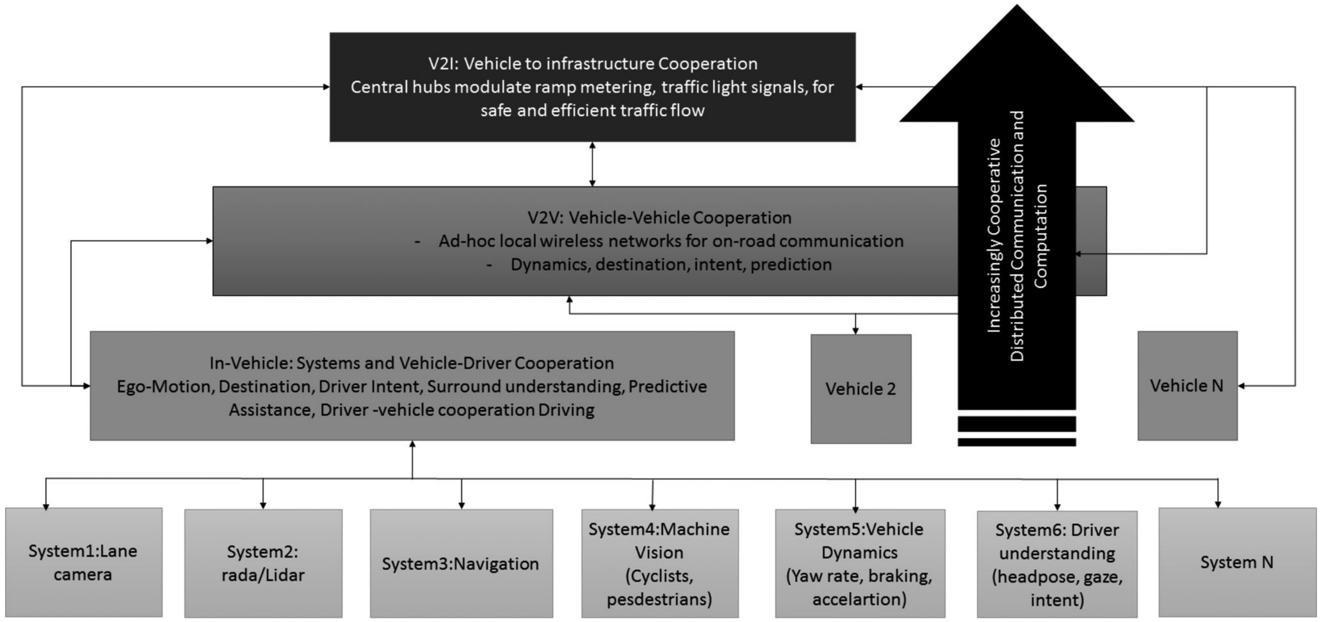

Fig. 8. Cooperative and predictive driver assistance: progression improvements [56].

driver in the gray car is momentarily distracted. Sensors in the street have detected an icy road condition, and this information is forwarded to the road infrastructure. The latter transmits it to the Cloud. Then, data are processed and pooled with actions of nearby cars (e.g., red car), location, and drivers states (distracted, impaired, and attentive). Analytics models can rapidly discern if a hazardous pending event is about to occur in this portion of the network. Consequently, the Cloud layer advise on the need for emergency services and the need for local authorities to deal with the icy road conditions. Immediately after, it alerts the driver of an imminent danger and recommends on possible actions to follow. In the case the driver does not respond in time, this alert triggers driver states monitoring systems safety measures in the gray car such as automatic braking or deceleration.

This illustrative scenario describes how driver states monitoring systems can be more efficient by being a component of the Internet of Cars. This integration should reduce road casualties caused by driver distraction. A new trend of these systems sees the distracted driver as an entity in a fleet of connected cars that is continuously interacting with its surroundings. This new trend termed as integrated safety, on which we focus in the next section.

B. Integrated Safety: The New Trend of Driver Monitoring Systems

It is worth noting that active and passive safety may reduce significantly the frequency of accidents and injury severity, but it is may not be sufficient. Fusion of pertinent information from the environment of the car helps to assess the current situation and identify the presence of a threat. The authors in [57] demonstrate that focusing only on cognition and behavior of the driver is not sufficient. It is crucial to account for behavior and traffic beyond the driver's vehicle.

The progression of safety systems improvements is depicted in Fig. 8. The lowest level of safety includes in-vehicle sensors that cooperate for enhanced performance. Second level integrates communications among vehicles using V2V. This is the cooperation safety across cars. The third level adds the cooperation between vehicles and infrastructure using V2I. Consequently, by integrated safety, we consider all possible cooperation between vehicles, traffic systems, infrastructure, and Cloud to mitigate accidents and maintain a full awareness of dangerous situations [2], [56]. This can be achieved by the following.

1) Driver centric techniques: ADAS ensures situational awareness and include the driver in the decision process.
2) Vehicle centric techniques: use of more sensors embedded in the vehicle to provide decision support.
3) Network centric techniques: use of plethora of wireless communications (V2X) to share pertinent information about the route, weather, and surrounding drivers.

The research community has shown great interest lately in integrated safety. Salvucci focuses on car interactions in [57]. They exploit computational cognitive models to predict and detect complex interactions between several cars, while one or more of the drivers are performing distracted driving. The results show that distracted driving can produce significant effects on other drivers. Hence, the driving distraction can be detected using drivers interactions. From the fact that distracted driver may have contribution to the average behavior of the population of cars, Ersal *et al.* [58] use a radial-basis neural network to model this aspect. In [59], the authors propose a cooperative ADAS (CoDAS) that tackles blind spot occurrence. Current blind spot assistance systems suffer from limited perception range in the scenario of fast passing cars. The main two components of CoDAS are the application unit (AU) and the car communication unit (CCU). The CCU sends and receives V2X messages from AU through its 802.11p radio interface as depicted in Fig. 9.

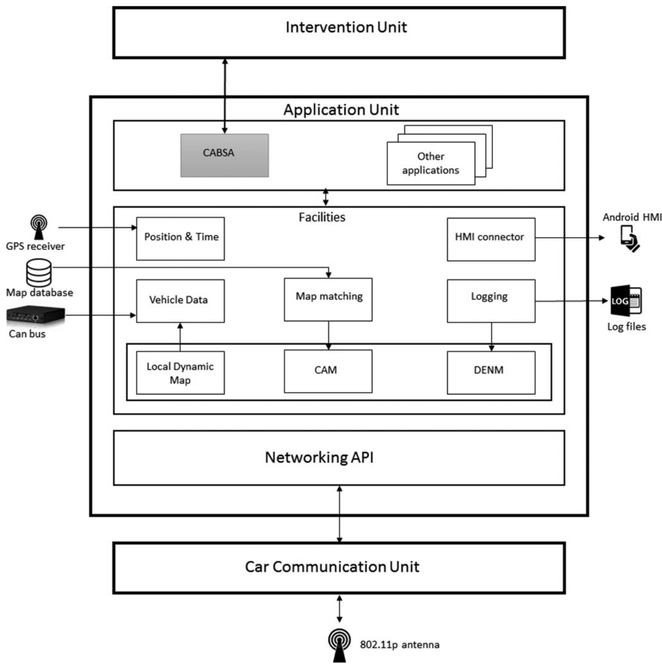

Fig. 9. CoDAS system architecture [59].

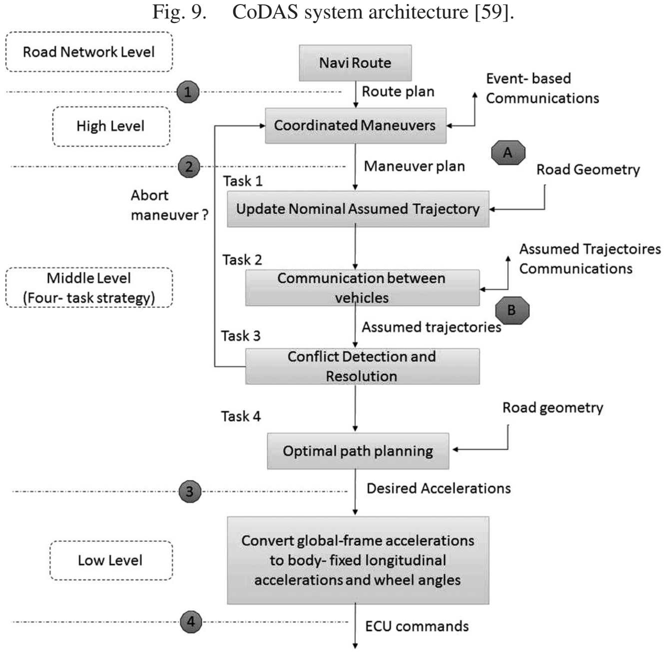

Fig. 10. Cooperative driving software framework residing on each vehicle [60].

In [60], the critical decision making process is shared between controlled close formations of cars, called a "platoon," via V2X communications. Their proposed framework (see Fig. 10) ensures platooning path planning and collision avoidance. The middle layer is a four-task strategy for path planning, which requires exchange of assumed trajectories via V2V communications between neighbors cars. Messages contain information on position, velocity, and acceleration profiles of cooperative vehicles for the next 5 s.

In [61], the authors propose a holistic attention assist framework (AFF) that encompasses the main aspects of integrated

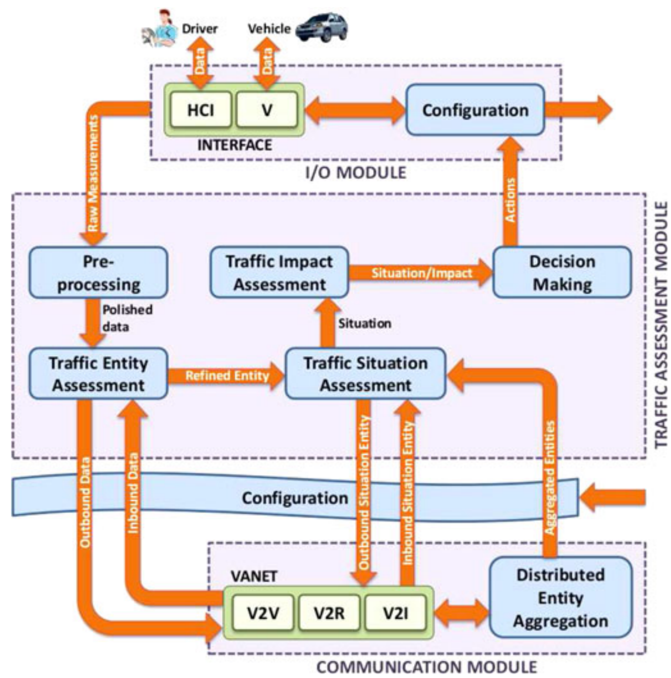

Fig. 11. Block diagram of AAF [61].

safety and models them using the high-level information fusion techniques. Since a smart city provides a myriad of information sources, the AFF takes advantage of this rich set of information to provide a more accurate traffic situation assessment. A block diagram of the proposed framework is depicted in Fig. 11. Three basic modules, namely I/O module (IOM), traffic assessment module, and communication module cooperate tightly to execute the whole process.

V. Discussion and Future Directions

In this section, we highlight some specific research directions that appear promising or are likely to be challenging in the coming years.

A. Autonomous Driving

Since the vast majority of accidents are caused by human errors (distracted and impaired driving), automakers want to transfer as much as possible the risk from the driver to the machine. A self-driving car can be defined as a car, which can achieve perception of its driving environment, make decisions about its path to reach destination, and, finally, drive toward the destination without substantial intervention of human. The driver inattention detection technologies could bridge an important gap in the realization of autonomous or self-driving cars. When the attention of human drivers is established, cars can be made autonomous on relatively safe road, and whenever more precise handling is required, driving control can be returned to humans. In a different scenario, when a driver inattention is detected, cars will run autonomously and avoid roads that require precise handling.

1) Autonomous Cars Today: Google was self-driving pioneers [62]. Its self-driving car has driven over 435 000 miles on California roads in April 2013. Mercedes-Benz developed an autonomous car, called the S 500 Intelligent Drive research vehicle in August 2013. The self-driving car succeeded to drive for 100 km in dense traffic and complex traffic situation [63]. Volvo Tech is working on a project that aims at making trucks smarter and able to completely take over the driving task [64]. The project is based on a predictive 360° view of things that allows the truck to make decisions based on what it thinks about its surroundings.

A recent collaboration between the U.S. space agency and Nissan targets the development of a fleet of autonomous cars that can drive without human intervention in real driving conditions [65]. Besides, BMW unveiled a car that can, via an application installed on a smart watch, find a parking garage and a spot without any human support [66].

The first test of self-driving car in open public road was held in Parma, Italy, in July 2013 [67]. The test included roundabouts, pedestrian crossings traffic light, junctions, and road priority. Nevertheless, some problems still unsolved such as large roundabouts and bad weather conditions.

2) Challenges for Driver Assistance Systems: It is not certain how self-driving technology will shape safety systems embedded in the car. Based on currently available data, we are confident that it will have a drastic impact on future ADAS systems. We nevertheless highlight the following challenges.

1) *Need for sophisticated environment model:* While it is obvious for humans to navigate in urban streets, it may not be a straightforward task for future autonomous cars. Navigating safely requires sophisticated models of the environment around self-driving cars, recognition techniques of other surrounding vehicles and obstacles, and best practices to navigate without breaking any traffic rules.
2) *Adaptation and improvement of road infrastructures:* Self-driving cars need maps drastically different from what we use today to navigate. Maps in future should be updated every second about road conditions, obstacles, lane closures, accidents, and traffic streams. Maps makers should use data provided by RSUs and data in the cloud to feed maps in real time. This is becoming a reality for a number of luxury cars, which are connected with the Internet.
3) *Specific human–machine interaction (HMI) requirements:* By hitting roads in few decades, autonomous cars will define new HMI concepts and mental models. Users in robotcars understand differently the autonomous cars directions and warning. Therefore, the new concepts and models should take into account this huge diversity. In addition, the role of the driver, the driver–car interaction, and driver involvement should also be investigated.

B. From ITSs to Data-Driven ITSs: How Big Data Is Revolutionizing Driving Monitoring Systems

The volume of data that is generated by drivers, cars, road infrastructures, or on-board sensing units is overwhelming. In fact, transportation networks offer a variety of infrastructural information ranging from weather, construction areas to dynamic roadway condition. Moreover, cars can receive and transmit near-range information using V2V and V2I communications such as obstacles behind curves and slow-driving vehicles. Local information are also gathered by on-board sensing units such as video cameras, LIDAR, and radar units (obstacles ahead and lane deviation). According to recent studies [68], 26 millions of connected cars have generated more than 480 TB of data. This number keeps rising as more information and data are generated around connected cars. In the other hand, self-driving cars will use a huge number of sensors to gather real-time information about the car, the driver, and its changing surroundings. Those sensors will work tightly with a constellation of other technologies such as LTE, 5G, clouds, and electric grids [69]. Hence, managing petabytes of information is now the new norm, and data are at the core of traffic and safety authorities decisions.

1) Big Data Collection and Predictive Analysis: The amount of structured and unstructured data created by connected cars, as well as the plethora of its sources and complexities, represents the main issues for the introduction of big data paradigm in ADAS systems [69]. With connected cars, data collection technologies are moving from traditional means such as loop detector or video detections to in-car telematics, technologies that leverage connectivity whether over the Internet or via dedicated short -range communication devices. Connectivity will not only boost existing in-car technologies such as event data recorders or on-board diagnostic standards, but connectivity will shape drastically the data collection technologies outside the car [70]. This ocean of data can only be beneficial and generate significant traffic safety advices if multiple sources of data are paired and data are mined and assessed correctly. This raises the question: how to interpret this huge volume of data and how to inform drivers in case of critical situations?

Analyzing the data will capture real-time data insights from inside and outside the cars and ensure revealing meaningful driving patterns or connections between driving behavior and specific driving situations. That is the role of predictive analytics. This latter will enable fleet managers to use data to switch from a historical descriptive view to a forward-looking perspective of what is ahead [71].

2) Improving Driver Safety Through Big Data: We think that Big data will bring new revolutionary ways to learn how drivers actually behave to mitigate accidents and assist drivers during their journeys. To name a few:

1) *Connected driver assistance:* Big data analytics can provide high-level insight into driver personality by capturing, his way of moving, his way of switching lanes, how hard drivers push brake systems, at what speed, and the conditions under which they are applied. Recently, INRIX has developed the INRIX Road safety technology that gives drivers advance warning of dangerous road weather conditions ahead, keeping them safer on their route [72].
2) *Predictive health and diagnostic check:* Driven by predictive analytics, predictive maintenance software can detect anomalies and failure patterns in car's functioning mode. This early revelation of potential threats ensures the deployment of limited resources for maintenance, the extension of equipment uptime, and ultimately improving driver satisfaction [73].
3) *Smart mobility:* By tracking driver behavior data and mixing against traffic data, weather conditions and

social networks information (concert, closed road, etc.) can also help drivers to make more smarter driving decisions. The analysis of this mixture of pertinent data can provide drivers unique insights regarding the types of roads in his trip and traffic conditions [74], [75].

4) *Cost-effective autoinsurance:* Traditional rating factors used by cars insures, such as age, gender, marital status, driving violations, credit score, and previous claims experience, are not enough efficient. To measure the true level of driver risk, they need to track the risk level of drivers' daily commutes and their daily actions on the road. These data combined with other information (weather, traffic volume, road conditions, etc.) are used to rate the driving skills and hence attribute a more accurate score to the driver. Based on these scores, cars insures will determine the insurance charge for each driver.

Big data is the fuel of connected vehicles. Combining the connected car, the data it generates, and big data analytics would fundamentally shift the way of making decision from a reactive mode to proactive intelligence in decision making.

C. Security and Privacy Issues in Internet of Cars

The privacy implications of connected cars come from the underlying technologies used in Internet of Cars. Telematics and other connected car services are delivered using a combination of technologies including on-board vehicle sensors, GPS satellite communications, V2V and V2I communications, cloud computing, and data analytics. These technologies will gather, analyze, and make use of high volumes of data from a variety of sources. Hence, the wireless transmission of data as well as its passage through the cloud makes it readily and constantly available to the automaker.

Moreover, despite its benefits mentioned in the previous paragraph, big data raise big concerns about the amassing of huge information and their use to identify individuals from supposedly anonymous datasets and to glean intelligence about drivers and passengers [76]. Subsequently, connected cars present unique privacy issues not only because the environment in which cars evolve, but also because of the additional data that connected cars generate. Some of the highly sensitive information are biometric and health data, location data, personal communications (voice, email, social networking), personal contacts, and schedules. We will highlight hereafter the main factors that create issues for privacy and security.

1) *Massive and cumulative data combined with the power of data analytics:* The use of cumulative and combined vehicle's data could have devastating consequences on personal data. Before the emergence of big data and cloud, the knowledge of a given piece of personal data (driving routes, in-vehicle communications, etc.) reveals limited information about the driver.
2) *Risks of overcollection:* Drivers cannot hamper the automakers to harvest and store their personal data in the cloud or data center unnecessarily. This situation increases dramatically the risks of vulnerability to security breaches, malicious access and use, state surveillance, and any other suspicious use from third parties. Only the relevant information for a specific purpose should be collected.
3) *Risks of in-vehicle system maintenance:* A connected car will need to download updates similar to smartphones or computers. Typically, the car will establish a connection to a cloud-based system to get updates in order to avoid repairs on the road. Hence, the security of a car and its data connections are no longer limited to the in-vehicle environment.

VI. Conclusion

Driver errors still remain the main cause of casualties in the roads. Texting at the wheel, talking in the cell phone, checking maps, and drowsiness are different types of activities that take the driver away from his primary task of driving and decreases drastically his attention. Thus, it is fundamental to investigate driver inattention behavior behind the wheel. This was the purpose of the first section of our paper. Indeed, we provided a comprehensive classification of different types of inattention. For each type, we gave a complete state of the art of frameworks that mitigate driver inattention.

On the other hand, the paradigm of Internet of Cars is fast becoming a reality. Main goal still remains driving without fatalities. In Internet of Cars, vehicles will talk (communicate) to drivers, road users, traffic signs, roads, and Cloud. Therefore, a special attention was given to integrated safety, since it integrates driving states monitoring systems with a constellation of other technologies (LTE, 4G, V2V, V2I, etc.). Integrated safety ensures more accurate perception of the driver behind the wheel.

Finally, the last part provided insights on main challenges still encountered along with future directions of research in the area of driver state monitoring systems. These issues should be tackled and solutions should be found to ensure minimum injuries and fatalities on our roads. One of the most important trends is self-driving cars where the driver concept will vanish progressively to give birth to computer on wheels. Thus, governments and research institutions along with car manufacturers are requested to plan at all levels for making self-driving a reality on our roads.

References

[1] Association for Safe International Road Travel. Accessed Feb. 2015. [Online]. Available: http://www.asirt.org/

[2] A. Eskandarian, "Fundamentals of driver assistance," in *Handbook of Intelligent Vehicles*, A. Eskandarian, Ed. London, U.K.: Springer, 2012, pp. 491–535.

[3] M. Fogue, P. Garrido, F. J. Martinez, J.-C. Cano, C. T. Calafate, and P. Manzoni, "Automatic accident detection: Assistance through communication technologies and vehicles," *IEEE Veh. Technol. Mag.*, vol. 7, no. 3, pp. 90–100, Sep. 2012.

[4] M. A. Regan, C. Hallett, and C. P. Gordon, "Driver distraction and driver inattention: Definition, relationship and taxonomy," *Accident Anal. Prevention*, vol. 43, no. 5, pp. 1771–1781, 2011.

[5] S. G. Klauer, T. A. Dingus, V. L. Neale, J. D. Sudweeks, and D. J. Ramsey, "The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data," Nat. Highway Traffic Safety Admin., Washington, DC, USA, Techn. Rep. DOT HS 810 594, 2006.

[6] J. D. Lee, K. L. Young, and M. A. Regan, "Defining driver distraction," in *Driver Distraction: Theory, Effects, and Mitigation*. Boca Raton, FL, USA: CRC, 2008, p. 31.

[7] J. D. Lee, M. A. Regan, and K. L. Young, "What drives distraction? Distraction as a breakdown of multilevel control," in *Driver Distraction: Theory, Effects, and Mitigation*. Boca Raton, FL, USA: CRC, 2008, pp. 41–56.

[8] T. A. Ranney, E. Mazzae, R. Garrott, and M. J. Goodman, "NHTSA driver distraction research: Past, present, and future," in *Proc. Driver Distraction Internet Forum*, 2000, vol. 2000, [Online]. Available: http://wwwnrd.nhtsa.dot.gov/departments/Human%20Factors/driver-distraction/PDF/233.PDF

[9] Nat. Highway Traffic Safety Admin., "Overview of the national highway traffic safety administration's driver distraction program," Nat. Highway Traffic Safety Admin., Washington, DC, USA, Rep. DOT-HS-811-299, 2010.

[10] F. Tango, M. Botta, L. Minin, and R. Montanari, "Non-intrusive detection of driver distraction using machine learning algorithms," in *Proc. 19th Eur. Conf. Artif. Intell.*, 2010, pp. 157–162.

[11] F. Tango and M. Botta, "Real-time detection system of driver distraction using machine learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 2, pp. 894–905, Jun. 2013.

[12] M. Wollmer *et al.*, "Online driver distraction detection using long short-term memory," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 574–582, Jun. 2011.

[13] S. L. Gallahan *et al.*, "Detecting and mitigating driver distraction with motion capture technology: Distracted driving warning system," in *Proc. IEEE Syst. Inf. Eng. Des. Symp.*, 2013, pp. 76–81.

[14] J. Jo, S. J. Lee, H. G. Jung, K. R. Park, and J. Kim, "Vision-based method for detecting driver drowsiness and distraction in driver monitoring system," *Opt. Eng.*, vol. 50, no. 12, pp. 127202-1–1272022-4, 2011.

[15] M. Rezaei and R. Klette, "3D cascade of classifiers for open and closed eye detection in driver distraction monitoring," in *Computer Analysis of Images and Patterns*. New York, NY, USA: Springer, 2011, pp. 171–179.

[16] A. Azman, Q. Meng, and E. Edirisinghe, "Non intrusive physiological measurement for driver cognitive distraction detection: Eye and mouth movements," in *Proc. 3rd Int. Conf. Adv. Comput. Theory Eng.*, 2010, vol. 3, pp. V3–595.

[17] A. Ragab, C. Craye, M. S. Kamel, and F. Karray, "A visual-based driver distraction recognition and detection using random forest," in *Image Analysis and Recognition*. New York, NY, USA: Springer, 2014, pp. 256–265.

[18] C. Craye, "A framework for context-aware driver status assessment systems," Master's thesis, Dept. Electr. Comput. Eng., Univ. Waterloo, Waterloo, ON, Canada, 2013.

[19] T. Hirayama, K. Mase, and K. Takeda, "Detection of driver distraction based on temporal relationship between eye-gaze and peripheral vehicle behavior," in *Proc. 15th Int. IEEE Conf. Intell. Transp. Syst.*, 2012, pp. 870–875.

[20] Y. Liang and J. D. Lee, "A hybrid Bayesian network approach to detect driver cognitive distraction," *Transp. Res. C, Emerg. Technol.*, vol. 38, pp. 146–155, 2014.

[21] C. Craye, A. Rashwan, M. S. Kamel, and F. Karray, "A multi-modal driver fatigue and distraction assessment system," *Int. J. Intell. Transp. Syst. Res.*, vol. 14, pp. 173–194, 2016.

[22] F. E. Group *et al.*, *Options for Regulatory Approach to Fatigue in Drivers of Heavy Vehicles in Australia and New Zealand*. Canberra, Australia: Aust. Transp. Safety Bureau, 2001.

[23] H. Croo, M. Bandmann, G. Mackay, K. Rumar, and P. Vollenhoven, *The Role of Driver Fatigue in Commercial Road Transport Crashes*. Brussels, Belgium: Eur. Transp. Safety Council, 2001.

[24] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, "Driver inattention monitoring system for intelligent vehicles: A review," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 596–614, Jun. 2011.

[25] Y. Takei and Y. Furukawa, "Estimate of driver's fatigue through steering motion," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, 2005, vol. 2, pp. 1765–1770.

[26] J. Krajewski, D. Sommer, U. Trutschel, D. Edwards, and M. Golz, "Steering wheel behavior based estimation of fatigue," in *Proc. 5th Int. Driving Symp. Human Factors Driver Assessment, Training Veh. Des.*, 2009, pp. 118–124.

[27] R. Sayed and A. Eskandarian, "Unobtrusive drowsiness detection by neural network learning of driver steering," *Proc. Inst. Mechan. Eng. D, J. Automobile Eng.*, vol. 215, no. 9, pp. 969–975, 2001.

[28] T. Pilutti and A. G. Ulsoy, "Identification of driver state for lane-keeping tasks," *IEEE Trans. Syst. Man, Cybern. A, Syst. Humans*, vol. 29, no. 5, pp. 486–502, Sep. 1999.

[29] Y.-J. Zhong, L.-P. Du, K. Zhang, and X.-H. Sun, "Localized energy study for analyzing driver fatigue state based on wavelet analysis," in *Proc. Int. Conf. Wavelet Anal. Pattern Recognit.*, 2007, vol. 4, pp. 1843–1846.

[30] K. Torkkola, N. Massey, and C. Wood, "Driver inattention detection through intelligent analysis of readily available sensors," in *Proc. 7th Int. IEEE Conf. Intell. Transp. Syst.*, 2004, pp. 326–331.

[31] B.-G. Lee and W.-Y. Chung, "Driver alertness monitoring using fusion of facial features and bio-signals," *IEEE Sens. J.*, vol. 12, no. 7, pp. 2416–2422, Jul. 2012.

[32] J. He, S. Roberson, B. Fields, J. Peng, S. Cielocha, and J. Coltea, "Fatigue detection using smartphones," *J. Ergonom.*, vol. 3, 2013, Art. no. 120.

[33] D. Y. Jia and S. X. Zou, "Driver fatigue monitoring based on head and facial features using hierarchical Bayesian method," *Appl. Mech. Mater.*, vol. 548, pp. 1093–1097, 2014.

[34] T.-H. Chang and Y.-R. Chen, "Driver fatigue surveillance via eye detection," in *Proc. IEEE 17th Int. Conf. Intell. Transp. Syst.*, 2014, pp. 366–371.

[35] M. I. Khan and A. B. Mansoor, "Real time eyes tracking and classification for driver fatigue detection," in *Image Analysis and Recognition*. New York, NY, USA: Springer, 2008, pp. 729–738.

[36] X. Li, N. Tan, T. Wang, and S. Su, "Detecting driver fatigue based on nonlinear speech processing and fuzzy SVM," in *Proc. 12th Int. Conf. Signal Process.*, 2014, pp. 510–515.

[37] D. F. Dinges and R. Grace, "PERCLOS: A valid psychophysiological measure of alertness as assessed by psychomotor vigilance," Federal Highway Admin. Office of Motor Carriers, Washington, DC, USA, Tech. Rep. MCRT-98-006, 1998.

[38] W. Qing, S. BingXi, X. Bin, and Z. Junjie, "A PERCLOS-based driver fatigue recognition application for smart vehicle space," in *Proc. 3rd Int. Symp. Inf. Process.*, 2010, pp. 437–441.

[39] L. Li, M. Xie, and H. Dong, "A method of driving fatigue detection based on eye location," in *Proc. IEEE 3rd Int. Conf. Commun. Softw. Netw.*, 2011, pp. 480–484.

[40] X. J. Wang and X. H. Yuan, "Research of infrared video fatigue detection based on SoPC," *Appl. Mech. Mater.*, vol. 411, pp. 1488–1494, 2013.

[41] T. C. Chieh, M. M. Mustafa, A. Hussain, E. Zahedi, and B. Y. Majlis, "Driver fatigue detection using steering grip force," in *Proc. Student Conf. Res. Develop.*, 2003, pp. 45–48.

[42] A. Koesdwiady, R. Abdelmoula, F. Karray, and M. Kamel, "Driver inattention detection system: A PSO-based multiview classification approach," in *Proc. IEEE 18th Int. Conf. Intell. Transp. Syst.*, 2015, pp. 1624–1629.

[43] D. Kurian, K. Radhakrishnan, and A. A. Balakrishnan, "Drowsiness detection using photoplethysmography signal," in *Proc. 4th Int. Conf. Adv. Comput. Commun.*, 2014, pp. 73–76.

[44] T. Sone and T. Yagi, "Drowsiness detection by skin potential activity," in *Proc. 6th Biomed. Eng. Int. Conf.*, 2013, pp. 1–5.

[45] S.-J. Jung, H.-S. Shin, and W.-Y. Chung, "Driver fatigue and drowsiness monitoring system with embedded electrocardiogram sensor on steering wheel," *IET Intell. Transp. Syst.*, vol. 8, no. 1, pp. 43–50, 2014.

[46] C. Zhang, H. Wang, and R. Fu, "Automated detection of driver fatigue based on entropy and complexity measures," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 1, pp. 168–177, Feb. 2014.

[47] A. Picot, S. Charbonnier, and A. Caplier, "On-line detection of drowsiness using brain and visual information," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 42, no. 3, pp. 764–775, May 2012.

[48] G. Li and W.-Y. Chung, "Detection of driver drowsiness using wavelet analysis of heart rate variability and a support vector machine classifier," *Sensors*, vol. 13, no. 12, pp. 16 494–16 511, 2013.

[49] I. G. Daza, L. M. Bergasa, S. Bronte, J. J. Yebes, J. Almazán, and R. Arroyo, "Fusion of optimized indicators from advanced driver assistance systems (ADAS) for driver drowsiness detection," *Sensors*, vol. 14, no. 1, pp. 1106–1131, 2014.

[50] L. Li, K. Werber, C. F. Calvillo, K. D. Dinh, A. Guarde, and A. König, "Multi-sensor soft-computing system for driver drowsiness detection," in *Soft Computing in Industrial Applications*. Berlin, Germany: Springer, 2014, pp. 129–140.

[51] S. Al-Sultan, A. H. Al-Bayatti, and H. Zedan, "Context-aware driver behavior detection system in intelligent transportation systems," *IEEE Trans. Veh. Technol.*, vol. 62, no. 9, pp. 4264–4275, Nov. 2013.

[52] Y. Fangchun, W. Shangguang, L. Jinglin, L. Zhihan, and S. Qibo, "An overview of internet of vehicles," *Commun., China*, vol. 11, no. 10, pp. 1–15, 2014.

[53] L. Nanjie, "Internet of Vehicles: Your next connection," *win-win magazine*, (Dec. 2011). [Online]. Available: http://www1.huawei.com/enapp/28/hw-110836.htm

[54] M. Gerla, "Vehicular cloud computing," in *Proc. 11th Annu. Mediterranean Ad Hoc Netw. Workshop*, Jun. 2012, pp. 152–155.

[55] Bosch develops cloud-based wrong way driver warning system. (Accessed Mar. 2015). [Online]. Available: http://www.connectedcar-news.com/news/2015/sep/08/bosch-develops-cloud-based-wrong-way-driver-warning-system/

[56] S. Sivaraman and M. Trivedi, "Towards cooperative, predictive driver assistance," in *Proc. 16th Int. IEEE Conf. Intell. Transp. Syst.*, Oct. 2013, pp. 1719–1724.
[57] D. D. Salvucci, "Distraction beyond the driver: Predicting the effects of in-vehicle interaction on surrounding traffic," in *Proc. SIGCHI Conf. Human Factors Comput. Syst*, 2013, pp. 3131–3134.
[58] T. Ersal, H. J. Fuller, O. Tsimhoni, J. L. Stein, and H. K. Fathy, "Model-based analysis and classification of driver distraction under secondary tasks," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 3, pp. 692–701, Sep. 2010.
[59] O. Sawade, B. Schaufele, J. Buttgereit, and I. Radusch, "A cooperative active blind spot assistant as example for next-gen cooperative driver assistance systems (CoDAS)," in *Proc. IEEE Intell. Veh. Symp. Proc.*, Jun. 2014, pp. 76–81.
[60] D. Caveney and W. Dunbar, "Cooperative driving: Beyond V2V as an ADAS sensor," in *Proc. IEEE Intell. Veh. Symp.*, Jun. 2012, pp. 529–534.
[61] K. Golestan, R. Soua, F. Karray, and M. S. Kamel, "A model for situation and threat/impact assessment in vehicular ad-hoc networks," in *Proc. 4th ACM Int. Symp. Develop. Anal. Intell. Veh. Netw. Appl.*, 2014, pp. 87–94.
[62] Google self-driving car project. (Accessed on: Mar. 2015). [Online]. Available: http://www.google.com/selfdrivingcar/
[63] (Accessed Mar. 2015). [Online]. Available: http://next.mercedes-benz.com/en/autonomous-driving-in-the-tracks-of-bertha-benz/
[64] Volvo trucks. (Accessed Mar. 2015). [Online]. Available: http://spectrum.ieee.org/cars-that-think/transportation/safety/volvo-tech-makes-trucks-smart-enough-to-not-run-you-over
[65] Nissan Autonomous cars. (Accessed Mar. 2015). [Online]. Available: http://spectrum.ieee.org/cars-that-think/transportation/self-driving/nasa-and-nissan-chase-selfdriving-car-technology
[66] BMW car. (Accessed Mar. 2015). [Online]. Available: http://spectrum.ieee.org/cars-that-think/transportation/self-driving/car-park-thyself
[67] A. Broggi, P. Cerri, S. Debattisti, M. C. Laghi, P. Medici, M. Panciroli, and A. Prioletti, "Proud-public road urban driverless test: Architecture and results," in *Proc. IEEE Intell. Veh. Symp. Proc.*, 2014, pp. 648–654.
[68] (Accessed Mar. 2015). [Online]. Available: http://press.ihs.com/press-release/country-industry-forecasting/big-data-drivers-seat-connected-car-technological-advance
[69] The Internet on wheels and Hitachi, Ltd. (Accessed Mar. 2015). [Online]. Available: https://www.hds.com/en-us/pdf/white-paper/hitachi-white-paper-internet-on-wheels.pdf
[70] *The Connected Car and Privacy Navigating New Data Issues*, Future of Privacy Forum, Washington, DC, USA, 2014.
[71] *Predictive Analytics 101: Next-Generation Big Data Intelligence*, Intel IT Center, Santa Clara, CA, USA, 2013.
[72] *Improving Driver Safety Through Big Data*, INRIX, Kirkland, WA, USA, 2014.
[73] Prevent asset failure, detect quality issues and improve operational processes. (Accessed Mar. 2015). [Online]. Available: https://www-01.ibm.com/software/analytics/solutions///operational-analytics/predictive-maintenance/
[74] A. Koesdwiady, R. Soua, and F. Karray, "Improving traffic flow prediction with weather information in connected cars: A deep learning approach," *IEEE Trans. Veh. Technol.*, vol. PP, no. 99, 2016.
[75] R. Soua, A. Koesdwiady, and F. Karray, "Big-data-generated traffic flow prediction using deep learning and Dempster-Shafer theory," in *Proc. Int. Joint Conf. Neural Netw.*, 2016, pp. 3195–3202.
[76] *The Connected Car: Who Is in the Driver's Seat*, FIPA, Vancouver, BC, Canada, 2015.

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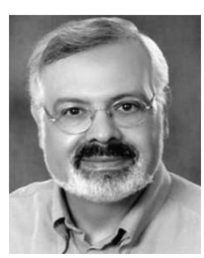

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