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Towards Next-Generation Vehicles Featuring the Vehicle Intelligence

Yasin Firat Payalan and M. Amac Guvensan

***Abstract*— Safe driving and minimizing the number of casualties are the main motivations of researchers and car companies for decades. They also care very much on saving fuel consumption and high comfort-level trips. With the help of advanced driver assistance systems (ADAS) applications, safer, more comfortable, and greener trips are very likely at the present time. However, today humankind is very close to make a very old dream, namely, driverless vehicles, to come true. In this paper, we address the concept of next-generation vehicles, their requirements, challenges, advantages, and problems. Regarding Society of Automotive Engineers (SAE), levels (1–5), we first define the crucial contexts for next-generation vehicles. We then discuss existing ADAS, their abilities, and available platforms which they run on from past to present. Next, we introduce a novel vehicle intelligence (VI) architecture consisting of ADAS modules and VI services which would pave the way for fully autonomous vehicles regarding not only driving issue, but also human-centric new demands such as entertainment and comfort level of the journey. The proposed conceptual design is built on sensors, vehicle ad hoc networks (VANETs), and big data. Afterward, we describe how current ADAS applications would transform on the way toward SAE Level 5 cars. We finally discuss the open issues for next-generation vehicles.**

***Index Terms*— Self-driving, advanced driver assistance system, vehicle intelligence, contexts and sensors for autonomous vehicle.**

I. Introduction

TRANSPORTATION has always been a crucial necessity for the survival of humankind. Today, we mainly exploit several types of vehicles including cars, buses, trucks, trains, trams, ferries, airplanes, motorcycles, bicycles, helicopters for the transportation. All technological advancement has led engineers to design remote and auto-controlled vehicles including drones, unmanned air vehicles, self-driving cars which are just the forerunner of a new era in the transportation history.

Safety is one of the most common issues during transportation. Thus, the researchers have been focused on preventing the accidents and enabling the safe transportation of driver, passengers and things. On the other hand, several reasons including the very-high number of vehicles on traffic, the increasing amount of expenses, the climate change, the high CO_2 emission ratios have led researchers to propose new solutions for economical driving [1]. Besides, researchers started to work on the comfort level of passengers and driver [2]. Long trip is one of the factor that directly affects comfort level. Both physical and nervous fatigue increase during long term trips according to Inagaki's research [3]. We believe that researches on driving comfort would help people to stay less tired especially after long trips. For safe trips, the big responsibility is taken by driver where he/she should continuously attentive during the whole journey. However, it is not easy to maintain his/her attention due to several reasons such as tiredness, loudness, sleepiness, and talking. This lack of attention may cause severe crashes resulting with injuries and/or even deaths. In order to prevent loss of attention, several kinds of ADAS are introduced to help/alert the driver [4].

Most traffic regulations aim at minimizing the number of crashes. However, the main reason for crashes are drivers as shown in Table II. i.e., driving quality explicitly affects the safety. Observing and evaluating driving behavior enables the drivers to drive carefully and thus it provides better comfort level as well as safety. Thus, driving quality assessment would help to classify driver as aggressive/non-aggressive or score his/her driving attitude.

Another critical safety issue is the health of mechanical and electronic components of vehicles. Without periodical maintenance, these components might break down easily while driving and it could lead to unexpected crashes. So that, intelligent human-machine interface should observe the vehicle components and proactively report failures in a vehicle.

All the aforementioned challenges, categorized in Table I could be solved via ADAS. Thus, vehicle companies have been focused on ADAS to ensure safety, comfort and economy for driver and passengers. Researches about ADAS have especially increased after the development of gasoline-powered vehicles. Advanced Driver Assisted Systems are the initial steps of self-driving autonomous vehicles. There are various autonomy-level described for next-generation vehicles. Society of Automotive Engineers (SAE) has described the autonomy levels for motorized vehicles, given in Figure 1. There are six different levels to indicate the autonomous capability of a vehicle. Wang's research [5] is explaining each level and giving vehicle examples engineered the aspect of the levels. Vehicle control mostly depends on driver, vehicle and environmental contexts. In Level 1 and Level 2 vehicles, context acquiring process frequently performed by the human driver. Few contexts are acquired by these vehicles themselves. For example, self-parking is a feature of Level 2 vehicle. Self-parking featured vehicles can automatically sense their

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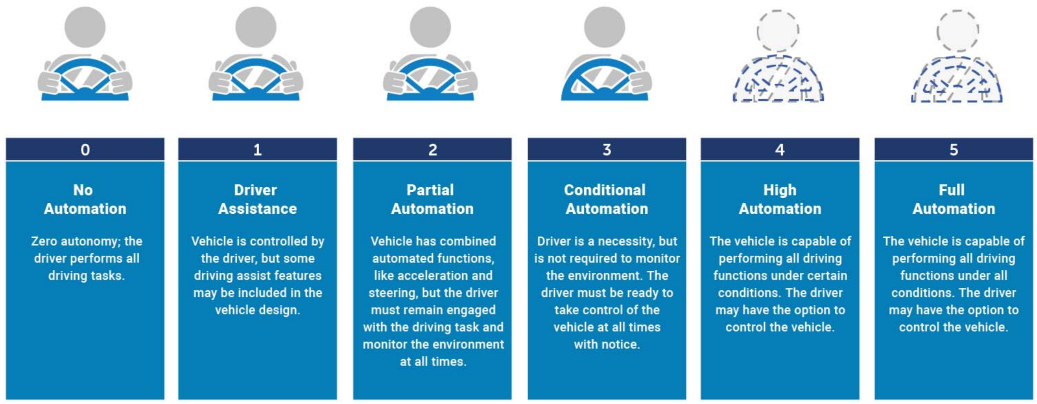

Fig. 1. Automation levels of motor vehicles [6].

environment while performing parking. Vehicles will achieve Level 5 when they would be able to reason all the contexts in the vicinity and make decisions without any help of driver even in the critical situations.

In order to design autonomous vehicles, researchers should first analyze and identify all the contexts about driver, vehicle, and inner/outer environment. Context understanding and reasoning are the key challenges of environmental-aware vehicles. Context reasoning is the process which exploits more than one contexts to derive new contexts for real world scenarios. Thus, we can say that context reasoning is the first step towards next-generation vehicles starting from SAE Level 3 [7]. In the last decade, some SAE Level 3 cars are introduced by different software and car companies. Waymo is Google' s self-driving car project that started in 2009. Waymo achieved SAE automation Level 3 in 2012 [8]. Tesla Autopilot is known as ADAS application [9] which has lane detection, ACC and self-parking capability. Tesla Autopilot product considered SAE Level 2 through these features. NVIDIA engineered self-driving feature as a platform to vehicle manufacturers. Audi A8 is the first Level 3 autonomous car with cooperation NVIDIA's partnership [10].

Vehicles are evolving while ADAS applications are increasing their skills. Most of the modern vehicles are being considered in level one and two of SAE autonomy level. They are introduced with self-parking capability [11], and are capable of managing the distance with leading vehicle [12]. Besides, new-generation vehicles are able to monitor driver condition to keep cruise safety [13]. These skills are just a few features of the commercially available ADAS applications offered with today's vehicles. However, the term "next-generation vehicle" is still not clearly defined. Researchers and car manufacturers are still questioning the definition of next-generation vehicle.

The main focus of this paper is to define the next-generation vehicle by explaining its main challenges, primary goals and existing/upcoming problems during the journey. From our perspective, next-generation vehicles will be capable of the four main issues including self/eco-driving, comfort, safety, and entertainment and meet the all the requirements of SAE Level 5. These type of vehicles would own several type of sensors, produce and process a bulk of data and thus, should be able to understand momentary contexts and make decisions based on their Vehicle Intelligence architecture. Vehicle Intelligence is the new proposed concept for next-generation vehicles which would be responsible for the safety, comfort, entertainment, and energy consumption simultaneously with the help of its task-specific modules and services built on sensor, VANET, big data infrastructure and existing and upcoming ADAS solutions. It is behind the well-known driving intelligence concept where the driving intelligence focuses only on route planning, real-time driving problems and abilities, i.e, driving intelligence would be a part of the Vehicle Intelligence in the future.

The contributions of this paper could be given as follows.

- The history of (Advanced) Driver Assistance Systems are given in detail.
- A new Vehicle Intelligence Architecture for next-generation vehicles is proposed by combining the available ADAS and a novice type of services, namely Vehicle Intelligence Services (VISs) to meet human-centric new demands.
- We also discuss open issues for next-generation vehicles regarding autonomy and context awareness.

This paper aims at presenting a new intelligence concept for next-generation vehicles considering the transforming transportation problem using a bottom-up approach. First, in Section 2, we introduce the fundamental contexts in Driver Assistance Systems in order to show the essential problems of next-generation vehicles. Then, in order to give the existing standalone solutions for the main challenges of traditional vehicles, Section 3 discusses the available Driver Assistance Systems, the ADAS platforms and the available sensors on them. The first concept vehicles show that autonomous driving would keep the main requirements of a journey. However, there would arise new demands especially for driverless trips. Thus, in Section 4, we first introduce SAE Levels and the capabilities of next-generation vehicles and then propose our Vehicle Intelligence Architecture for next-generation autonomous vehicles. Section 6 gives the open issues for next-generation vehicles. Then, we conclude the paper in Section 7.

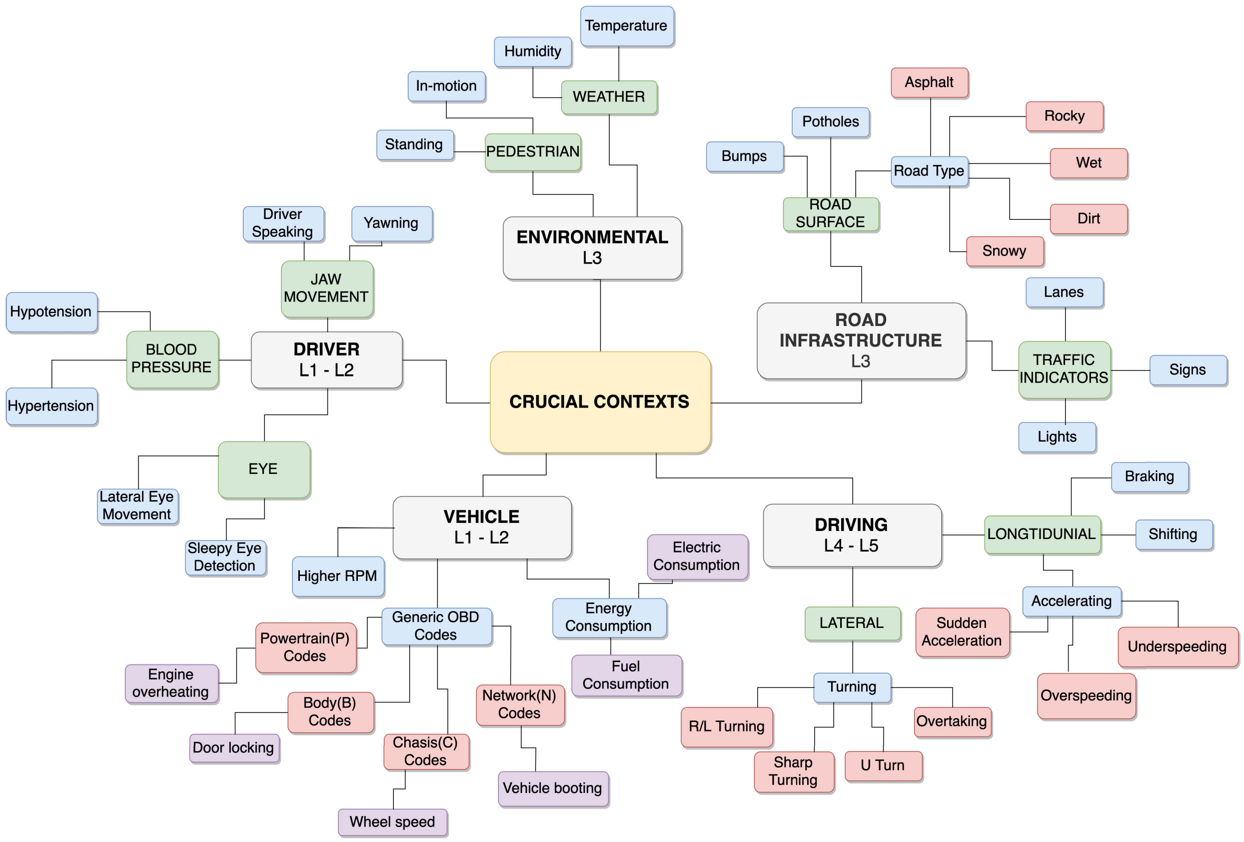

Fig. 2. Crucial contexts for vehicle intelligence with minimum requirement of SAE automation levels.

II. Fundamental Contexts for Vehicle Intelligence

Context-awareness is one of the important issue of intelligent transportation systems. Thus, researchers are focused on understanding the contexts for vehicle and drivers to design efficient and robust ADAS applications. Each context can implicitly or explicitly affect the assistance action. For example, driving inattention monitoring aims at detecting and warning sleepy and careless drivers. Especially, long-distance drivers could not keep their attention during long trips. In such tiring trips, the driver may fail to see a traffic sign. ADAS applications will compensate this failure and thus driving safety could be ensured automatically. On the other hand, some people might drive from time-to-time aggressively. The frequency of lateral and longitudinal [14] contexts can essentially determine the level of anger of a driver. These kind of contexts explicitly affect driving quality. Monitoring driver actions with the help of these contexts can provide better assistance.

There is a set of contexts that need to be identified while driving in traffic. Contexts for intelligent transportation systems could be classified into *Driving, Driver, Environmental/Road Infrastructure* and *Vehicle* categories. These fundamental contexts are illustrated in Figure 2. The most important thing is not only to detect the context but also to associate different contexts, in order to design reliable and intelligent Driver Assistance Systems. The most popular contexts at traffic environment are given in Table I. In Table I, we also list the context category, related ADAS applications, the primary motivation of understanding corresponding context and related references regarding SAE Automation Levels.

A. Driver-Based Contexts

Understanding driver-based contexts are only possible by processing data collected from the driver. Human activities and conditions in a vehicle need to be tracked by Vehicle Intelligence, since either passengers and/or driver could appear in different status during a journey. We believe that driver-based contexts are very important because Level 4 and Level 5 autonomous vehicles aim at handling any kind of situation without any help of a human driver. We structured the driver-based contexts regarding the activities and status of driver and passengers in Table I. On the other hand, some ADAS applications have already partially achieved this objective for Level 1-3 autonomous featured cars.

Drowsiness Detection is a popular ADAS application that processes the visual data of the driver's face. It obtains information about driver's physical and mental status. Tracking movements mainly involve motion detection of face parts. For example, driver fatigue level can be measured by eye state tracking. Also, eye blinking gives an important clue about driver's drowsiness situation. Zhang designed a drowsiness detection system based on driver's eye blink frequency [95]. Lateral eye movement is an important indicator of safe driving. Trivedi [96] tracked eye gaze positions before lane has been changed by the driver. He also uses head dynamics to increase the drowsiness detection quality. However, eye state tracking

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TABLE I
THE IMPORTANT VEHICULAR ENVIRONMENT CONTEXTS AND THE RELATED ADAS APPLICATIONS

D: Driver, DRIV:Driving, V: Vehicle, E: Environmental						
Context Name	**Contribution to SAE Automation Level**	**Context Category**	**Primary Objective**	**Secondary Objective**	**Related to ADAS Application**	**References**
Driver Status						
intoxication	3	D	safety	comfort	Driver Drowsiness Detection	[15]
yawning	3	D	safety	comfort	Driver Drowsiness Detection	[16], [17], [18], [19], [20], [21]
accelerated / decelerated heartbeat	3	D	safety	comfort	Not Available	[22], [23], [24]
sleepy eye	3	D	safety	comfort	Not Available	[25], [26], [27], [28], [29]
eye movement	3	D	safety	comfort	Not Available	[30]
Disruptive Activities						
cell phone in use	3	D	safety	comfort	Cell Phone Detection	[31], [32], [33], [34]
cell phone handheld/ handsfree in use	3	D	safety	comfort	Not Available	
excessive smoke	3	D	safety	comfort	Not Available	
excessive noise	3	D	safety	comfort	Not Available	[35]
Longtidunial Driving						
overspeeding	2	DRIV	safety	efficiency	Driver Monitoring	[36], [37]
accelerating / decelerating	2	DRIV	safety	comfort	Lane Departure Warning, Driver Monitoring	[38], [39], [40], [41]
approaching an uphill	3	DRIV	safety	comfort	Hill Start Assist	[42]
approaching traffic light	3	DRIV	safety	comfort	Traffic Sign Detection	[43], [44], [45], [46]
coasting	3	DRIV	safety	efficiency	Not Available	
underspeeding	2	DRIV	safety	comfort	Driver Monitoring	
sudden braking	2	DRIV	safety	comfort	Driver Monitoring	[40], [47]
normal braking	2	DRIV	safety	comfort	Drowsiness Detection,Driver Monitoring,Road Condition Detection	[26], [48], [36], [49]
Lateral Driving						
lane changing	2	DRIV	safety	comfort	Collision Avoidance	[50]
right/left turn	2	DRIV	safety	comfort	Driver Monitoring,Navigational Systems	[40], [47]
sharp turn	4	DRIV	safety	comfort	Driver Monitoring	[51], [52]
u turn	4	DRIV	safety	comfort	Driver Monitoring	[53]
Incorrect Driving						
improper passing	4	DRIV	safety	efficiency	Not Available	
wrong side of road	4	DRIV	safety	efficiency	Not Available	
improper turning	4	DRIV	safety	efficiency	Not Available	
car collision	4	DRIV	safety	efficiency	Not Available	
unsafe lane changing	4	DRIV	safety	efficiency	Not Available	
head-on collision	4	DRIV	safety	efficiency	Not Available	
sideswiped collision	4	DRIV	safety	efficiency	Not Available	
rear end collision	4	DRIV	safety	efficiency	Not Available	
broadside collision	4	DRIV	safety	efficiency	Not Available	
hit a non-vehicle object	4	DRIV	safety	efficiency	Not Available	
hit a pedestrian	4	DRIV	safety	efficiency	Not Available	
overturning	4	DRIV	safety	efficiency	Not Available	[54], [55]
traffic congestion	3	DRIV	safety	efficiency	Not Available	
to overtake	4	DRIV	safety	comfort	Collision Avoidance, V2V	[56], [57], [50]
to be overtaken	4	DRIV	safety	comfort	V2V	[57], [58]
approaching a vehicle	3	DRIV	safety	comfort	V2V,Collision Avoidance	[59], [58], [60]

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TABLE I

(Continued.) THE IMPORTANT VEHICULAR ENVIRONMENT CONTEXTS AND THE RELATED ADAS APPLICATIONS

D: Driver, DRIV:Driving, V: Vehicle, E: Environmental						
Context Name	**Contribution to SAE Automation Level**	**Context Category**	**Primary Objective**	**Secondary Objective**	**Related to ADAS Application**	**References**
Longtidunial Driving						
approaching an intersection	4	DRIV	safety	comfort	V2V,Navigational Systems,Traffic Sign Detection,Driver Monitoring,Intersection Assistant,Pedestrian Detection	[26], [61], [62], [45], [63], [64], [65], [66], [67], [68]
sudden braking	2	DRIV	safety	comfort	Driver Monitoring	[40], [47]
R/D/N/L shifting	2	DRIV	safety	comfort	Not Available	
Pedestrian						
pedestrian crossing at non-intersection	3	E	safety	comfort	Not Available	
pedestrian crossing at intersection	3	E	safety	comfort	Pedestrian Detection	[69]
pedestrian passing by side	4	E	safety	efficiency	Not Available	
Road Condition						
bumps	3	E	safety	comfort	Speed Bump Detection	[70]
rocky road	3	E	safety	comfort	Not Available	
wet/dirt road	3	E	safety	comfort	Road Condition Detection	[71], [72]
entering a road	3	E	safety	comfort	Road Condition Detection	[41], [73], [74], [75]
potholes	3	E	safety	efficiency	Pothole Detection	[76], [77]
entering a railroad	3	E	safety	efficiency	Not Available	[78]
road construction	3	E	safety	efficiency	Not Available	[79], [80]
Weather						
clear weather	3	E	safety	comfort	Not Available	
foggy weather	3	E	safety	comfort	Not Available	[81], [82], [83]
windy weather	3	E	safety	comfort	Not Available	
raining/snowing	3	E	safety	comfort	Not Available	[84]
time of day	3	E	safety	comfort	Not Available	
Traffic Indicators						
traffic signal detecting	3	E	safety	efficiency	Traffic Sign Detection	
high beam detection	3	E	safety	comfort	Not Available	[85], [86]
Vehicle						
approaching a school bus	4	E	safety	efficiency	Vehicle Classification	
approaching a public bus	4	E	safety	efficiency	Vehicle Classification	
detecting ambulance	4	E	safety	efficiency	Vehicle Classification	
detecting fire truck	4	E	safety	efficiency	Vehicle Classification	
detecting improper driver	5	E	safety	comfort	Driver Monitoring	
detecting blind spots	4	E	safety	comfort	Blind Spot Detection	[87], [88]
Vehicle Interior						
seat belt taken/ removed	3	V	safety	efficiency	Seat Belt Detection	[89], [90]
baby on board	3	V	safety	efficiency	Not Available	
airbag deployed	1	V	safety	efficiency	Not Available	
radio on/off	3	V	safety	comfort	Not Available	
passenger count in vehicle	5	V	safety	comfort	Not Available	[91]
Vehicle Troubles						
low engine oil	1	V	safety	efficiency	Not Available	
engine overheating	1	V	safety	efficiency	Not Available	
spoiled battery	1	V	safety	efficiency	Not Available	
low windshield washer fluid	1	V	safety	efficiency	Not Available	

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TABLE I

(Continued.) THE IMPORTANT VEHICULAR ENVIRONMENT CONTEXTS AND THE RELATED ADAS APPLICATIONS

D: Driver, DRIV:Driving, V: Vehicle, E: Environmental						
Context Name	**Contribution to SAE Automation Level**	**Context Category**	**Primary Objective**	**Secondary Objective**	**Related to ADAS Application**	**References**
Vehicle Troubles						
low engine oil	1	V	safety	efficiency	Not Available	
engine overheating	1	V	safety	efficiency	Not Available	
spoiled battery	1	V	safety	efficiency	Not Available	
low windshield washer fluid	1	V	safety	efficiency	Not Available	
tire pressure low	1	V	safety	efficiency	Tire Pressure Monitoring	
tire boom	1	V	safety	efficiency	Not Available	[92]
drivetrain trouble	1	V	safety	efficiency	Not Available	
transmission malfunctioning	1	V	safety	efficiency	Not Available	
low brake fluid	1	V	safety	efficiency	Not Available	
steering fluid trouble	1	V	safety	efficiency	Not Available	
steering locked	1	V	safety	comfort	Not Available	
engine faults	1	V	safety	efficiency	Not Available	
inoperative exhaust gas sensor	1	V	efficiency	safety	Not Available	
unsealed gas cap	1	V	efficiency	safety	Not Available	
malfunctioning catalytics converter	1	V	efficiency	safety	Not Available	
low engine cooling	1	V	efficiency	safety	Not Available	
suspension malfunctioning	1	V	safety	efficiency	Not Available	
EV low battery	1	V	efficiency	safety	Not Available	
dirty diesel particulate filter	1	V	efficiency	safety	Not Available	
vehicle start/stop	1	V	efficiency	safety	Not Available	
engine start/stop	1	V	efficiency	safety	Not Available	
limitated electric engine power	1	V	efficiency	safety	Not Available	
car horn	3	V	safety	comfort	Not Available	[93], [94]
driver pose	3	V	safety	comfort	Not Available	[68]

may be inadequate in some cases to give drowsiness information about the driver. Wearing sunglasses can prevent to detect eye and disrupt eye state tracking. As yawning is another important clue for drowsy driver detection, detecting yawning could help to overcome this type of disruptive events. Several image processing techniques have been proposed to determine the drowsiness level of driver [18], [19]. On the other hand, drowsiness could also be evaluated through physiologic measurements. The heart rate varies significantly between the different stages of drowsiness, such as alertness and fatigue [17]. Electroencephalogram (EEG) is commonly used to measure drowsiness [16]. Also, Electromyogram (EMG) is another technique to detect drowsiness situation of the driver. Akin mentioned that combination of EEG and EMG had detected more reliable results of driver drowsiness situation [97].

Lateral motions of the vehicle are critical contexts that should be carefully managed. Wing mirrors are one of lateral driving control instruments. Drivers should frequently check wing mirrors to aware upcoming cars. Drivers also check mirrors to take a safe position at traffic environment. This kind of driver actions should be monitored to ensure safe driving conditions. On the other hand, some disruptive activities in a vehicle can ruin drivers' attention. Making phone calls, texting or talking to passengers are dangerous activities since it could cause severe crashes due to distractibility. Vollrath has analyzed adverse effects of speech activities while driving [98]. ADAS application should watch and manage speaking activities to prevent crashes.

B. Environmental and Road Infrastructure Contexts

Environmental detection is the baseline for Level 3 autonomous capability. Vehicles must aware of its surroundings regardless of shape, type and condition. We categorized environmental contexts regarding the domains which have an impact on driving safety and comfort. Weather has significant importance on road safety [99]. Road condition is an important factor to affect driving quality [100]. Also vehicles must be aware of pedestrians and traffic signs to keep safety.

Understanding environmental context is more challenging objective in ADAS applications. Exterior objects in vehicular environments such as other vehicles, pedestrians, traffic signs/lights, roads should be carefully sensed/analyzed to take immediate action against road infrastructure and environmental conditions changing dynamically. Sensors including LIDAR, RADAR, and visual cameras are heavily used to be aware of these environmental contexts [101]. Moreover, several autonomous test vehicles necessarily include these sensors to adapt themselves to dynamic environment conditions [102]. Drivers may not sustain their awareness continuously. ADAS technologies can sense/track these exterior objects and give feedback as informative or warning responses to the driver to bring his/her attention and to keep road safety.

Traffic signs are valid worldwide and if the driver fully complies with the traffic rules, the number of accidents could be definitely reduced. However, studies noticed that drivers become attentive at some traffic control devices better than others; drivers mostly notice speed limit signs, while pedestrian crossings signs are mostly overlooked [103]. Traffic Sign Detection applications aim to detect these traffic boards and lights. Thus, careless drivers could be warned before a dangerous situation arises. In the literature, several vision-based techniques [103], [104] are commonly used to detect traffic signs.

Pedestrians are also an important context for ADAS applications and as well as autonomous vehicles. Moreover, understanding pedestrian contexts can help drivers to keep better driving experience. Vehicles capable of pedestrian detection may able to notify driver while a pedestrian is passing in front/rear of a car. In [105], the authors implemented an assistance system that vehicle can automatically brake while pedestrian suddenly comes along and the driver could not respond. There are a bunch of studies dealing with this problem and several publicly available datasets such as Caltech [106], KITTI [107], INRIA [108]. Recently, deep learning techniques are becoming widespread to detect pedestrian with a higher performance. In [109], Zhang mentions that ConvNets are giving more strong results than other Convolutional Neural Network algorithms.

Road condition is one of the dynamic factors in environmental contexts. Driving attitude may change based on concrete, rocky or not a well-maintained road. Rough roads could contain some potholes and being not able to avoid from these holes could age vehicles and increase the probability of accidents. Retrieving information by analyzing road conditions would feed ADAS systems. Dangerous road conditions [49] and potholes [76], [77] could be given as different contexts that need to be perceived while driving. A well-defined assistance system can acquire these contexts and notify other drivers to keep road safety. Degenerated road contexts could also be shared with authorities for helping them on repairing the damaged roads.

C. Driving-Based Contexts

Driving action contains the primary characteristics of driver behavior. We need to understand vehicular motions as well as drivers habits for Level 3 even for Level 4 and Level 5 featured vehicles in order to evaluate the quality of a human driver and Vehicle Intelligence Architecture respectively. The fundamental driving actions are formed into Table I and defined as driving-based contexts.

With the help of sensors such as accelerometer and gyroscope several driving contexts such as braking, turning, stopping, starting to drive, could be easily detected [65], [110]. On the other hand, driving contexts mostly depend on the interaction of the driver with the environment. Environment knowledge is also significant to acquire driving based contexts. Turning is a simple lateral vehicle motion. When turning events associated with the direction obtained from a digital map, information of 'right turning' or 'left turning' contexts could be acquired.

Driver monitoring (DM) applications frequently use driving based contexts with respect to Table I. Driving identification is one of DM processes [65]. DM applications collect driving contexts and extract fingerprint information via machine learning techniques [111]. Car fleet companies use this feature to detect unauthorized drivers.

There are several studies and applications [65], [112] both to measure the driving quality and label/score drivers based on some metrics as well as to differentiate aggressive and non-aggressive drivers. This kind of applications can objectively measure driving safety level of drivers. They push drivers to safe driving and reveals aggressive driving patterns according to driving based contexts.

D. Vehicle-Based Contexts

Current vehicular diagnostic interfaces can detect malfunctions and errors. Nevertheless, Level 4 and Level 5 vehicles will be able to perform actions independently when any kind of system failure occurs. Some pre-actions is required to prevent unexpected failure of vehicle's mechanical parts. Monitoring core parts of a vehicle will likely resolve this issue. On-board diagnostics (OBD) trouble codes are currently operating this issue. OBD systems obtain sensor data from inside the vehicle and monitor the health condition of a vehicle part. Each unhealthy vehicle part is represented by "Trouble codes". The Trouble codes can be interpreted as vehicle-based contexts. For example; 'P2503-Charging System Voltage Low' has been accepted as 'vehicle battery failure' [113]. In modern vehicle systems, a simple LED light informs driver when malfunctioning appears. Especially in vehicles starting from Level 3, vehicular based contexts are remotely notified to the vehicle operator or authoritative units and people. Emergency planning techniques may be discussed when vehicular based failures have emerged in fully autonomous vehicles.

III. Advanced Driver Assistance Systems

Attributes of reflex and attentiveness are directly related to motor and cognitive performance of a human-being. Thus, driving performance is strictly based on a combination of motor and cognitive behavior of the driver. Driving performance varies by age, gender and health issues. Some environmental and emotional factors or fatigue can also adversely affect driving performance. Driving performance errors and distractions are major reasons of the driver related problems. Distraction increases in environments with less traffic according to Naturalistic Driving Studies(NDS) data. Cell phone usage, touchscreen panel interaction on a vehicle while driving also cause distractions which end up with crashes more than 50 percent of total number [114]. Driving behaviours should be carefully analyzed. Dingus' paper pointed that failing to

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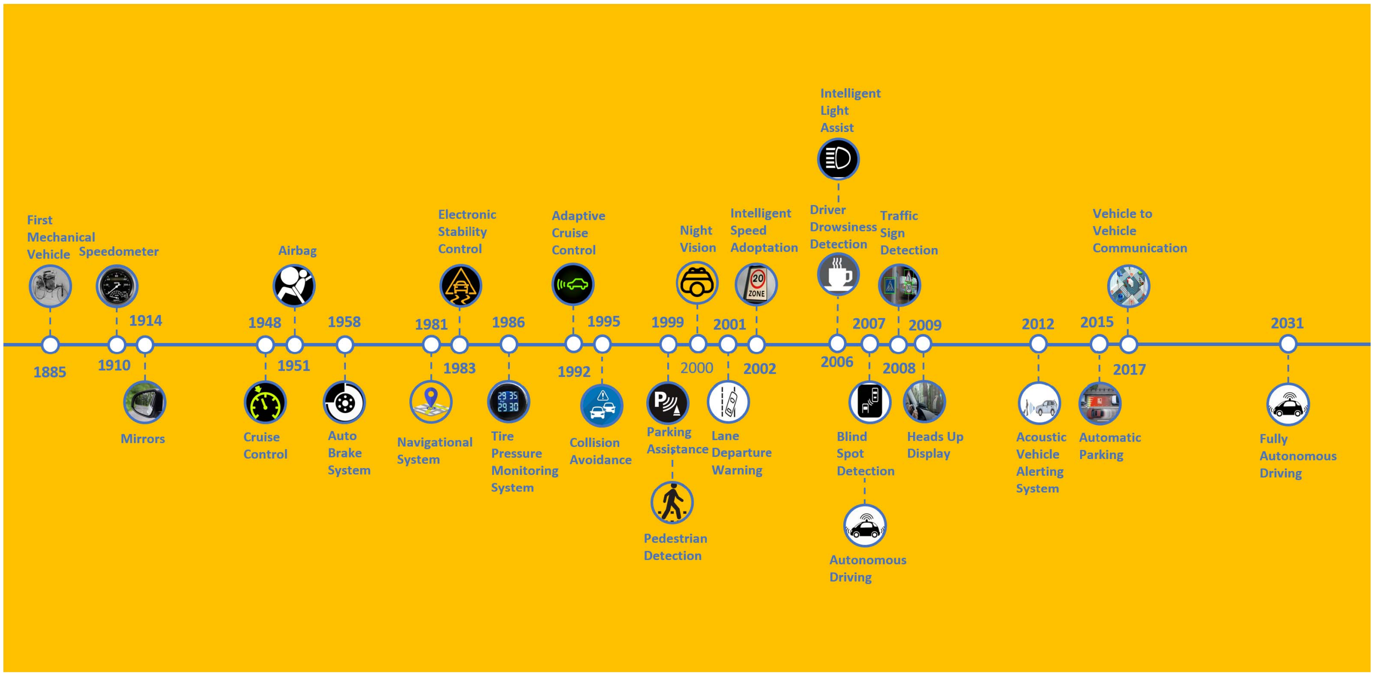

Fig. 3. The milestones of driver assistance applications.

signal, too slow driving and improper turnings are relevant to driving performance issues which increase crash risk by 18.2% [115] Most of the traffic accidents happen due to driver based problems as given in Table II. Safe driving precautions are crucial to minimize these accidents. ADAS, shown their historical progress in Figure 3, mainly aim to keep safety for drivers, passengers, pedestrian, animals and other things [116]–[118].

ADAS applications primarily aim to increase the safety and comfort and as well as to decrease the fuel consumption, as shown in Figure 4. In our opinion, efficiency and comfort issues ensure implicitly safe driving. We define efficiency as a traffic management and driving style. Since ADAS applications help to fix misbehaviour in traffic, we believe that efficiency and safety will improve in the future. The comfort of passengers is also an important issue, especially for long trips. People quickly get tired when the driver uses brake pedal too much or (de)accelerates suddenly. These kind of behaviors influence both efficiency and comfort issues negatively. Comfortable driving depends on the least effort possible while driving [2]. In this paper, we mostly focus on (un)comfortable driving contexts. Uncomfortable driving may occur in extreme road contexts such as dirty road or snowy weather. Understanding/handling/notifying environmental contexts would help drivers to give their attention much more on driving. Drivers are getting tired of these uncomfortable driving experiences. This tiredness could bring accidents inevitably.

ADAS applications should advise energy efficient, and environment protected driving. Eco-driving term encapsulates objectives of minimizing fuel consumption and reducing environmental toxic gases. Researchers have been magnified about ADAS applications which encourage drivers to eco-driving [63], [119].

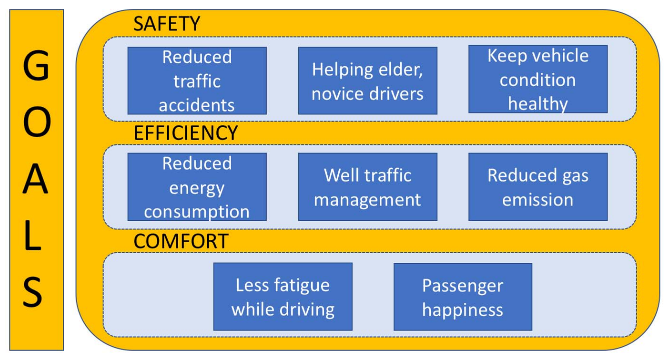

Fig. 4. Primary goals of ADAS.

The primary objective of ADAS applications is to ensure the safety of everything including people, animals, and other vehicles in the traffic environment. Speed limiting could be given as one of the first Driver Assistance systems. Authorities aim to prevent over-speeding within hilly conditions and bendy roads. This initial ADAS provides safe driving both on hilly environments and roads with curves. Today, this technology has evolved into adaptive cruise control (ACC) systems. Drivers whose car have ACC system can stabilize the vehicle speed with selected speed rate. This stabilization especially helps the driver to rest on long and straight roads.

There are three main topics which cover safety issues of ADAS. These topics are given as follows:

- Environmental Dynamics
- Vehicle Condition
- Driver Behaviour

Each object in traffic environment is potentially risky to vehicles. On the other hand, the road condition is also a crucial environmental factor for safe driving. Vehicles need

TABLE II
CRASHES BY REASONS [122]

reason	number	percentage
driver	2046000	94%
vehicle	44000	2%
environmental	52000	2%
other	47000	2%

to be robust according to challenging surface conditions. Potholes or damaged roads are malicious road contexts that can easily distract drivers attention and cause unsafe behaviors if not perceived. Potholes are one of the significant problems located on road surfaces. Drivers may not distinguish this kind of damaged roads. A well-defined assistance system [76], [77], [120] can recognize such environmental dynamics and notify the driver to keep traffic safety. We can also autonomously inform these potholes to authorities to help for fixing damaged roads using crowdsourcing technique. Tecimer's work can recognize those potholes using intrusive techniques [121].

Stress-free drivers always contribute to a smooth traffic environment. Stress caused by emotional disturbance, intoxication, exhaustion, drowsiness could disrupt the driving behavior. The best way to measure stress level of a driver is to observe driver and understand driving contexts. Acquiring driving related contexts are less intrusive. Some ADAS applications create profiles using well-driven actions and assist to the driver to comply this profile. This profiling relies on fingerprinting of driving events [36]. According to National Highway Traffic Safety Administration's report on 2015 94% of traffic accidents are based on driver related reasons [122] as represented in Table II.

Vehicle related crashes do not happen as frequent as driver related ones [122]. Nevertheless, monitoring mechanical parts of the vehicle is an important issue for safe driving. It proactively protects the driver from crashes. Light Emitted Dioedes(LED) lights, gauges are basic display systems for this action. Nowadays, Heads-Up Display systems are emerging through the Augmented Reality technology [123]. Another monitoring application is traffic regulations. The regulations are the most known application for vehicle monitoring. Traffic administration of some governments force drivers to periodically maintain their vehicles. Governments and vehicle manufacturers are still developing new regulations for next-generation vehicles.

Vehicle monitoring become more critical for Hybrid and electric vehicles(EV). The battery is a significant component of EV because it is fed by only its embedded and limited battery. Vehicle monitoring systems at EV's may efficiently calculate energy consumption and anticipate before drained. This issue has been presented by Rezvanizaniani, Liu, Chen, and Lee with an article that reviews safety aspects of battery monitoring techniques [124].

Comfort is another quality parameter of driving. It is not critical as safety. However, from the perspective of passenger, driving comfort hold higher importance. Car manufacturers have also developed ADAS applications which improve the driving experience with better driving comfort. Adaptive Cruise Control(ACC) adjusts the speed according to distance to the frontal vehicle. Minimum accelerating, braking actions, and adjusted distance have given comfortably driving experience.

Efficiency is the third goal in ADAS applications. Vehicle resource management or traffic management are two categories for efficiency. Better ADAS applications can maintain fuel consumption with making suggestion on better driving practicals. Reducing traffic abnormalities affect traffic environment obviously. As we mentioned before, ADAS applications can keep safe driving. This safety will reduce traffic accidents and provide better traffic management. The future goal of ADAS applications is to enable self-driving vehicles. We will discuss the details how the role of ADAS applications will change in next-generation vehicles in Section 4.

A. ADAS Platforms

Smartphone [110] and IoT based [125] solutions are the common platforms of Advanced Driver Assisted Systems. Many ADAS applications are implemented via smartphones [65], IoT devices [126], embedded in-vehicle solutions [127]. However, ADAS applications running on these devices have some bottlenecks. The common problem with all solutions is collecting the data. Sensor systems become a notable part of this activity. The primary sensors used by ADAS applications are shown in Table III. Sensors in a vehicle can continuously collect both internal and external states of the vehicle. Vehicle health condition, driving based metrics (speed, steering angle) are represented as an internal state, whereas environment-related variables (weather, temperature, road condition) are represented as an external state of the vehicle. Vehicle sensors can be categorized into proprioceptive and exteroceptive sensors [46]. Proprioceptive sensors mainly collect data about internal state of the vehicle such as speed, tire pressure, engine temperature, whereas exteroceptive sensors are mainly collecting environmental data like weather info, road surface, presence of static and dynamic objects. Both smartphones and embedded devices have necessary exteroceptive and proprioceptive sensors on them. There is a trade-off about some aspects such as general programming and system architecture challenges between these two kind of devices. For example; implementation on smartphones is easier than IoT devices. However, energy is a severe bottleneck for applications running on smartphones.

Due to several reasons such as low-cost, easy development, user-friendly interface, several driving assistant systems [110], [128] are implemented on smartphones. Smartphones involve lots of sensors that are suitable for context-acquiring system development. Some researchers are used accelerometer, magnetometer and location sensors to acquire driving contexts [40], [129]. Besides, a smartphone has many communication protocols to enable the sharing of data. Variety of these protocols can maintain communication much easier. For example; Bluetooth protocol is used for receiving data from CAN-bus, whereas road information, traffic congestion or emergency events could be notified to smartphones using the network connection with near real-time delay.

TABLE III
THE PRIMARY SENSORS BEING USED IN ADAS APPLICATIONS

Sensor	Related Contexts	Well-Known ADAS Applications							
		Drowsiness Detection	*Traffic Sign Detection*	*Navigation Systems*	*Driver Monitoring*	*Lane Detection*	*Pedestrian Detection*	*Collision Avoidance*	*Road Condition Detection*
Accelerometer	Driving Vehicle Environmental	[135]–[137]			[52], [65] [110], [129]	[138]			[76], [100]
Camera	Driver Driving Environmental	[95], [139]	[45] [101], [140]		[129], [141]	[41], [142] [143]	[117], [144] [145]	[146], [147]	[100], [120]
Biomedical Sensors	Driver, Driving	[148], [149]			[149]				
GPS	Driving Environmental			[150], [151]	[52], [110] [129]	[142], [143]			[100]
Gyroscope	Driving Environmental				[52], [110] [129], [152]	[138]			
LIDAR	Environmental		[101]	[143]			[153]	[147]	
Proximity	Driver	[154]							
V2V	Environmental		[155]						[155]

Currently, researchers and manufacturers are still taking advantage of embedded solutions compared to smartphone applications. The most important reason is that embedded solutions are more customizable although their implementation is difficult. Waite and Oruklu have made a Traffic sign recognition system with FPGA-based device [130]. Many car manufacturers are using embedded solutions for parking, avoiding collisions and detecting lanes [131], [132]. Embedded solutions have many advantages over smartphone-based solutions. One significant advantage is its energy consumption. Most of the embedded solutions exploit vehicle battery. However, smartphones have quietly reduced battery capacity. This bottleneck also prevents computational intensive context acquiring jobs. Security is another important advantage of embedded solutions. Regardless of operating system products [133] smartphones currently have many security vulnerabilities and these could end up with dangerous results such as giving access to unauthorized users who want to alter the control of vehicle [134]. Embedded solutions involve dedicated hardware and software systems. This characteristic helps to minimize reverse engineering procedures. Especially car manufacturers prefer embedded solutions to have the entire control over their products and to maximize the security level.

Sensor processing solutions will be offered in aspect of the autonomous vehicle domain. We mentioned that context-acquiring is one of the key process to enable the autonomous driving functionality. Apart from prototype Level 3 vehicles, current vehicles have still Level 1 and Level 2 SAE automation skills. These vehicles must perform environmental detection for SAE Level 3 automation skill. Context-acquiring systems, i.e. ADAS applications, can help Level 1 and Level 2 vehicles to increase their automation skills even in the future, since the automation technology would cost highly for a long time.

IV. NEXT-GENERATION VEHICLES

We have explained the fundamental contexts and also related ADAS applications in the perspective of the Society of Automotive Engineers(SAE) automation levels. Our literature review shows that existing vehicles could ensure only the requirements of Level 1, Level 2 and Level 3. Regarding this fact, from our perspective, Level 4 and Level 5 vehicles can be described as "next-generation vehicles". In this section, we conceptually discuss the SAE Levels 4 and 5 and introduce our Vehicle Intelligence architecture to meet the requirements of high automation and full automation.

SAE has segmented the automation level of a vehicle into six categories [156].

- Level 0 - No Driving Automation
- Level 1 - Driver Assistance
- Level 2 - Partial Driving Automation
- Level 3 - Conditional Driving Automation
- Level 4 - High Driving Automation
- Level 5 - Full Driving Automation

Apart from Level 3 vehicles, Level 4-5 vehicles should handle fall-back scenarios itself while automated driving is executing [157]. For example; a Level 3 vehicle might not respond when an animal is on the road. In such cases, a human driver takes the control of the vehicle. On the other hand, Level 3 vehicle could not perform self-driving feature when the vehicle leaves its pre-defined route, since all the driving opearations are designed based on the pre-defined route. However, Level 5 vehicles have to independently perform driving tasks regardless of the route.

Major changes such as vehicle material, energy type and self-driving feature are expected to happen for next-generation vehicles [158]. The self-driving feature would definitely bring some safety issues. Scholette's survey reveals possibly safety concerns on self-driving vehicles [159]. On the other hand, driving experience would change, since human would quit his/her driver role and would ride as a passenger whole the time. Thus, people could spend this time based on their pleasure in next-generation vehicles [156]. Several entertainment services would be offered to improve journey experience on self-driving vehicles. We believe that the

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next-generation vehicles would apply SAE's Level 5 autonomy level to adapt themselves to the expected changes. Therefore, we propose a novel Vehicle Intelligence architecture for next-generation vehicles in order to satisfy SAE's level-five autonomy.

Next-generation vehicles would definitely have sensor processing capability to acquire a wide range of contexts such as given in Table 1. Level 3 vehicles could only operate its automated driving session in a limited area. Thus, different routes consisting of various objects and events could not be driven for Level 3 vehicles [160]. This limitation would be overcome when self-driving vehicles could reason all the contexts given in Table I regardless of its route. Next-generation vehicles would also perform actions in any possible crash scenarios. Context sharing is an important necessity to accomplish these actions. For example; a self-driving vehicle will automatically send a message to emergency units when an accident occurs. Vehicles can also use context sharing to consume less energy and get context information from the vehicles in the vicinity that the physical sensors cannot obtain. Some optical sensors on self-driving vehicle could not obtain context information when the vehicle in high speeds and reduced inter-vehicle spacing environment [161].

Intelligence will be the core part of next-generation vehicles. Most ADAS systems will be integrated into the part of decision making and feed it with information obtained from the environment, in-car, driving conditions, driver, and passengers. The quality of vehicle intelligence module highly depends on the awareness of context diversity. The proposed VI architecture would be able to acquire the contexts of passenger, vehicle, and environment while driving. We believe that for high and full autonomous vehicles, contexts should be reasoned and stored within a particular device. This device could make out more reliable and objective clues during trips, especially at traffic accidents. Blackbox devices, also named Event Data Recorders (EDRs) are placed into vehicles to complete this task. Blackbox technology commonly used in avionics, military fields to examine the contexts and store records of critical moments such as just before crashes. Acquired contexts will explain what exactly happened before an incident occurs. Currently, some insurance and fleet management companies have used EDR's to measure the quality of driving and execute vehicle health-check. Ingenie [162] is the commercial product which is acquiring speed, brake, accelerate and cornering driving events stamped with location and time contexts. On the other hand, there is a non-commercial EDR that records driver events and determines driving behavior for calculating driving quality presented in [163]. Event Data Recorders are suitable especially for post-crash forensics applications. They are used to reveal the parameters that cause to accident. The traffic accident happened at Massachusetts in 2011 has shown the necessity of an EDR. [164]. Although the driver had claimed that he had been wearing his seatbelt before the accident, the EDR data had proved the driver to be wrong. EDR devices should be embedded into the vehicle. These kind of embedded EDRs are hardly accessible both on hardware and software. Only legal authorities can access the device, and give regulatory compliance to EDR products.

Although collection of data is important for context-awareness and safer trips, sharing this information has even higher impact on preventing accidents. Therefore, communication capability enables vehicles more intelligent. Vehicles, road units, infrastructures will be able to share practical information via Vehicular Ad Hoc Networks (VANETs). IEEE has defined a VANET implementation, labeled as a 802.11p protocol [165] that make the vehicles share information with another vehicle(V2V), road unit(V2R) or an infrastructure(V2I). This implementation also provides enhanced safety and efficient driving. There are several scenarios where VANET could play an important role. Nowadays compulsive techniques are used to detect another vehicle or road unit via image processing algorithms. For example; driver limits its speed while entering the road that signed with speed limit sign. Some traffic sign detection ADAS applications recognize it with the help of image processing [166], [167]. However, traffic signs are generally permanent objects, and we could inform the driver about the sign location without having any visual angle with the traffic sign. We can efficiently deliver the sign info using VANET technology via transmitting the type of sign info to the up-coming vehicles. Traffic management is much more accessible with VANETs. For example, road-side units can detect incidental conditions within traffic environment [168]. VANETs would provide information exchange between vehicles and other static or dynamic traffic objects. ADAS applications could react collaboratively after VANET integration [58]. Platooning can be an example of information exchanging over ADAS systems. Context sharing between units at traffic environment could reduce the cost of context acquiring. For example; when IoT equipped pedestrian shares its existence context to passing vehicles along the road using VANET, vehicles can afford the minimal cost to acquire pedestrian existence context. However, in contrast to VANET, image processing techniques are still very popular although they are very costly to acquire pedestrian context.

In our paper, we can state that future vehicles will acquire their contexts with dedicated hardware like EDRs and share their contexts via VANETs. These two requirements, also valid for SAE Level 4 and Level 5 vehicles, for safe transportation will definitely reduce human-related risks as much as possible. Therefore, both technologies are the key parts of next-generation vehicles.

A. Vehicle Intelligence Architecture

Driver Assistance Systems are intended to assist the human driver. Advanced DAS applications acquire contexts and then inform the driver accordingly. Besides, ADAS applications could solve more complex problems rather than DAS [169]. Some ADAS applications like ACC (Advanced Cruise Control) and Parking Assist can control the vehicle using context information. Assistance issue is changing and evolving with upcoming autonomous vehicles. The role of a human driver in the autonomous vehicle is not yet clear, since fully autonomous cars would not need a human driver. However, some legal and social concerns may push driver to be present in the vehicle during the ride. The human driver will substitute with the artificial intelligence concept in full autonomous vehicles. Nagai et.al. has already called this intelligence as Driving Intelligence [170]. We believe that Driving Intelligence would be responsible for driving actions and be a core part of Vehicle Intelligence. ADAS applications in autonomous vehicles have been categorized into Perception and Planning domains [171]. A vehicle has surrounded with many static (road condition, traffic sign, buildings) and dynamic objects (pedestrian, moving vehicles, animals) during its trip. The autonomous vehicle would be able to sense these kind of environmental objects and reason several contexts using its perception skill. On the other hand, planning is the core problem of autonomous robotic systems [172]. An autonomous vehicle should operate its driving session using the shortest and safest way. Current navigation systems can compute the shortest way for a given source and destination point. Unexpected situations such as sudden stops/lane changes, uncontrolled pedestrian/animal crossing could be very challenging for planning operation. Mission, Behavioral and Motion planning are described as three main parts of driving intelligence in an autonomous vehicle [173], [171]. Mission planning is responsible from calculating the shortest path from source to destination using instantaneous traffic information. Urmson has described Behavioral planning such that it is in charge of understanding driving and environmental contexts and deciding which motion goals will be taken on route [173]. Context knowledge of autonomous vehicle is essential for making harmonious move. Driving contexts can be categorized into impacts of efficiency and comfort issue. Motion planning is responsible for achieving motion goals reported by behavioral planning module. Detecting bumps, unhealthy road conditions, obstacles, lanes are critical contexts that are necessary for execution of motion planning [171]. We believe that especially Level 5 self-driving vehicles will totally change driving experience because a self-driving vehicle can completely perform the driving action. Current driving intelligence architectures are inadequate for Level 4 and Level 5. Some relevant works introduce driving intelligence architectures [170], [174] to achieve only autonomous driving capability especially in SAE Level 2 and 3 featured vehicles.

On the other hand there are some new requirements for high automation and full automation vehicles. For example; Level 4 vehicles must handle any kind of fall-back scenarios autonomously. Conventional vehicles use pre-crash ADAS applications to evaluate risky conditions. Many pre-crash systems detect fall-back scenarios [147], [175] but human driver must intervene to complete the action. Thus, we believe that new pre-crash applications are necessary for both detecting risky events and executing actions without human intervention in the future.

Next-generation vehicles will introduce new challenges. The most critical one is cybersecurity among them. A software-based architecture will execute the whole driving process and handle all kind of situations. Current software and hardware-based security problems and attacks [176] would spread to next-generation vehicles. The architecture of a next-generation vehicle should be designed regarding these

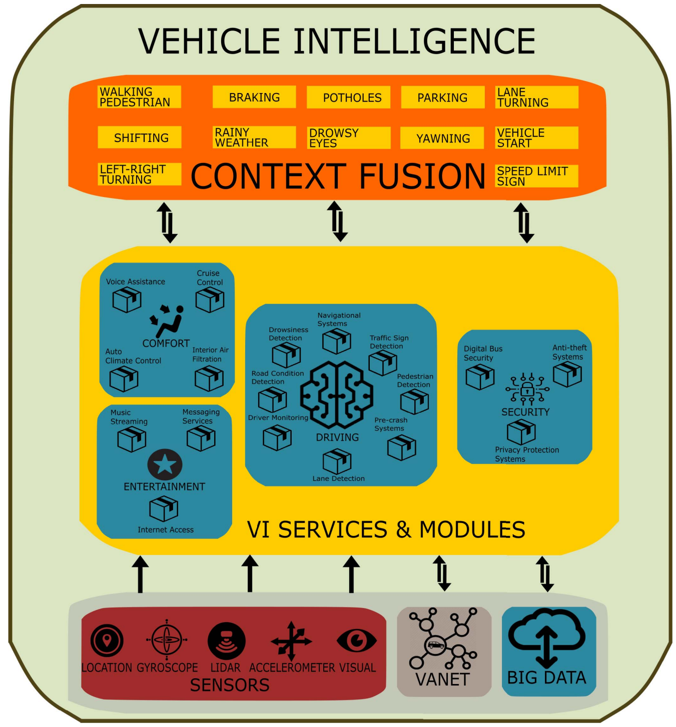

Fig. 5. The proposed vehicle intelligence architecture consisting of ADAS modules and VI services.

security issues in order to prevent the accident originating from software-based attacks. On the other hand, next-generation vehicles would offer several new services to enable the passengers spend their time pleased and productive. Passengers would have a lot of idle time to exploit these services. Thus, we believe that a vehicle intelligence architecture should contain entertainment services in the next-generation vehicles. The main shortage of current driving intelligence architectures [170], [174] is the absence of services such as comfort, security, entertainment which are expected to be built-in features of next-generation vehicles. Moreover, the existing architectures do not have a context fusion layer which enables the integration of existing ADAS applications in our architecture. In this paper, we introduce a new architecture for next-generation vehicles shown in Figure 5. Apart from other studies, we describe new Vehicle Intelligent Services for Entertainment, Security, Comfort in addition to Driving Intelligence concept. Driving Intelligence would be the primary component of next-generation vehicles and would administrate the whole journey from beginning until arriving the destination. From our perspective, current ADAS applications will contribute to the autonomy of next-generation vehicles [170]. Rather than to address all problems for self-driving, we believe that existing ADAS applications could be integrated to build a powerful Driver Intelligence for autonomous vehicle. However, this integration requires a context fusion layer where ADAS can exchange their obtained contexts. On the other hand, to enable comfy and amusing trips, autonomous vehicles would offer several supplementary services such as messaging, playing music and video, voice assistants, internet access. Besides, these vehicles would automatically adjust the oxygen level as well as the temperature based on passenger profiles.

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After all, the vehicle would protect itself against unauthorized usages by using bio-metric identification techniques and informing the vehicle owner.

The proposed architecture would ensure another important contribution which would be provided by VANET technology and Big Data analysis. In-Vehicle context sharing is so important for building a smarter Driver Intelligence, whereas Intra-Vehicle communication would enable collaborative info management to prevent crashes. On the other hand, analyzing big data collected from millions of vehicles would help us to suggest eco-driving options, alternative less-tiring routes, and estimate possible accidents which might happen in the vicinity. We believe that the proposed Vehicle Intelligence architecture would give a perspective to researchers who work on next-generation vehicles.

V. Open Issues

Researchers and car companies are focused to launch their first self-driving car as soon as possible. However, fully-autonomous vehicles are expected to be deployed by 2025 at the earliest. On the other hand, US Secretary of Transportation stated at the 2015 Frankfurt Auto show that he expects driverless cars to be in use all over the world within the next 10 years. In this manner, ADAS applications are the main steps towards next-generation vehicles. Drivers could experience safe trips with the help of ADAS applications such as Collision Warning and Lane Departure Warning (LDW) systems. We have so far introduced the off-the-shelf ADAS applications in this paper. In this chapter, we discuss the open issues for designing next-generation vehicles.

Core Design: Standalone working ADAS applications are evolving into cooperative and autonomous applications [177]. Although current conventional vehicles benefit from current ADAS applications, new platforms are expected to be designed to enable context fusion in the next-generation vehicles. Cost is another problem for next-generation vehicles. Some vehicular sensors are still expensive. Smartphones and IoT devices are relatively resolving this issue, but range-based sensors, such as LIDAR and RADAR are still not affordable for common use since these sensors have optical components which relatively expensive. Nevertheless, it is noteworthy that perception planning mostly relies on range-based sensors in autonomous vehicles. Most of the next-generation vehicles would have an Internet connection whereas current vehicles are connecting to the network over smartphones. With the help of connected vehicles, people will be able to reach entertainment content easily. Thus, we believe that there is an explicit requirement of ADAS applications which manage in-car entertainment services such as navigating, music streaming, reading book, recording speech/playing games.

Cloud Services: Next-generation vehicle would benefit from cloud services. Due to its limited computational resources, autonomous vehicles might not process big data especially the historical data to make predictions. Big data is one of the primary data sources for next-generation vehicles which we mentioned in Figure 5. Especially exploiting rich data sources such as weather info, road condition and traffic density data, would help to increase safety and comfort level as well as to decrease fuel consumption. However, this kind of data could be obtained from crowd and be stored at cloud servers. Thus, cloud services could provide valuable reports and predictive information to autonomous vehicles. Cloud services have an extensive capability of computing. Essential big data analysis would enable to predict potential accidents on a specific location before it occurs. The conscious driver normally might be aware of the characteristics of any road which has been driven before on. S/he can optimize his/her driving behavior on the well-known roads to minimize the risk of a traffic accident. However, an autonomous vehicle has theoretically no driver. It must have the latest and updated information about the road and must understand, detect and track other vehicles' contexts (overspeeding vehicles, intersections, traffic lights, passengers). Cloud services can compute and analyze all those information and will calculate the risk of accident on the road. Crowdsourcing and crowdsensing techniques should be exploited to increase the accident prediction probability. Some papers have already been integrated crowdsensing technique with cloud technology in order to predict traffic accidents and maintain traffic. [178], [179]

Computational Bottleneck: Thanks to powerful hardware components, current autonomous vehicles benefit from deep learning algorithms. Deep learning is a sophisticated form of Artificial Neural Networks. The complexity of deep neural networks relies on the number of both hidden layer and nodes in the neural networks. Thus, deep-layered networks can handle more complicated and bigger datasets. However, computational power of Central Processing Units(CPUs) is inadequate, since the primary objective of CPU is to orchestrate operating system resources. It is obvious that dedicated hardware is necessary to overcome this problem. Graphics Processing Unit(GPU) is the most suitable hardware component that most of deep learning algorithms run on [180]. On the other hand, specific hardware unit for next-generation vehicles is able to acquire and process multiple contexts at a single time. This device needs to be developed to cope with this computational bottleneck. Currently, one GPU manufacturer has engineered their autonomous car hardware unit [181].

Data Collection: Data collection is as crucial as context reasoning. Thus, EDR devices would become an essential part of the next-generation vehicles. Due to security concerns, all vehicle-specific and driving related data should be collected via EDR as we mentioned in Chapter 4. We believe that security and privacy [182] are the main challenges of EDR implementations. The data collected via EDR device must not be leaked or altered. EDR provides new intelligent traffic solutions. Various driver profiling and autonomous driving performance evaluation, crash risk prediction on specific road segments can be implemented according to EDR data. However, mobile phone applications might not be suitable for autonomous vehicles because smartphones have limited energy and security vacancies. Embedded hardware solution (a more specific IoT device) can resolve these two important issues.

Road Infrastructure: Since driving habits would change in next-generation vehicles, traditional road infrastructure would be insufficient for these vehicles. In order to prevent collisions and to resolve traffic issues, all the vehicles should communicate each other and to the roadside units. VANET is the most appropriate solution to enable this communication [161]. We believe that new type of road-side units should be designed and deployed to enable sustainability of full autonomous driving experience.

Simulations: Testing is a very challenging part of the engineering of self-driving cars. Also, it is very costly to generate some events such as accident, traffic congestion etc. in real life on the roads. Simulations can take a significant role to overcome this issue. We need much more scenarios to make ready next-generation vehicles even in urban areas. Simulators should model both the dynamics of Level 4 and 5 vehicles and urban roads conditions [183].

VI. Conclusion

Understanding of vehicular environment contexts such as crossing pedestrian, wet road condition, low tire pressure, and interacting to dynamic environment conditions are the main responsibilities of each ADAS application individually. Hence, next-generation vehicles equipped with a vehicle intelligence mechanism would orchestrate individual ADAS applications and comfort/entertainment/security services in order both to accomplish SAE Level 4 and Level 5 requirements/challenges and to improve the journey experience of passengers. Current self-driving vehicle frameworks are restricted into specific territories. However, the proposed VI architecture would enable the vehicles to drive in any environment. On the other hand, the Vehicle Intelligence architecture is designed also to meet new demands of passengers including entertainment, comfort level, and security for fully-autonomous vehicles. Since driving experience will totally change in the future and a human within fully autonomous vehicle will spend his/her time for personal issues, the proposed architecture would replace driving intelligence concept which only focuses on the driving issue. Our study shows that there would be vehicles with both AI driver and human driver on roads at the same time in the long future. This fact complicates the adaption of self-driving vehicles since there would be many human drivers who cheat the rules. Therefore, next-generation vehicles should be configured with a self-learning vehicle intelligence. This software would delegate the main tasks such tracking the environmental conditions, health/comfort of passengers and the conditions of vehicle parts to each ADAS and then process the results to make its final instantaneous decision. Each decision and its result should be feed to the system and help to be build an updated driving model. On the other hand, other information arrived from neighborhood vehicles, road infrastructures and cloud services which are responsible for making analysis about big data collected via crowd-sourcing techniques would be enabled with the help of VANET technology. VANET technology would also help to forward all the data collected via in-vehicle event data records to the big data center. We believe that big data analysis would increase the probability of estimating the possible incidents by warning the AI-driver for example to make the vehicle slow-down or change its lane. In the future, AI drivers would be scored like the human drivers and all software/car companies would compete for skillful self-driving vehicles. However, regulations are the big handicap for autonomous vehicles, since the answer of the question who will be responsible if there would happen any accident between self-driving cars is unclear.

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