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In-Vehicle Sensing for Smart Cars

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(Invited Paper)

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ABSTRACT Driving safety has been attracting more and more interest due to the unprecedented proliferation of vehicles and the subsequent increase of traffic accidents. As such the research community has been actively seeking solutions that can make vehicles more intelligent and thus improve driving safety in everyday life. Among all the existing approaches, in-vehicle sensing has become a great preference by monitoring the driver's health, emotion, attention, etc., which can offer rich information to the advanced driving assistant systems (ADAS) to respond accordingly and thus reduce injuries as much/early as possible. There have been many significant developments in the past few years on in-vehicle sensing. The goal of this paper is to provide a comprehensive review of the motivation, applications, state-of-the-art developments, and possible future interests in this research area. According to the application scenarios, we group the existing works into five categories, including occupancy detection, fatigue/drowsiness detection, distraction detection, driver authentication, and vital sign monitoring, review the fundamental techniques adopted, and present their limitations for further improvement. Finally, we discuss several future trends for enhancing current capabilities and enabling new opportunities for in-vehicle sensing.

INDEX TERMS Artificial intelligence, advanced driving assistant systems (ADAS), distraction/inattention, driver authentication, fatigue/drowsiness, in-vehicle sensing survey, occupancy detection, smart car, vital sign monitoring, wireless sensing.

I. INTRODUCTION

The last several decades have witnessed the unprecedented proliferation of automobiles, which has contributed greatly in our daily commute, economy, business and entertainment [1]. According to the American Automobile Association (AAA) [2], there are roughly about 1.2 billion vehicles operating on the planet every day with an average trip of 15 minutes. The in-vehicle time grows up to 46 minutes per day in the United States [3]. While we have benefited a lot from the tremendous number of motor vehicles, it has been shown [4] that the road accidents cause approximately 1.3 million deaths every year and about 20–50 million more non-fatal injuries, many of which incur a lifelong disability [5]. Among those accidents, about 94% –96% of them are related to some human error [6].

To improve driving safety, many efforts have been devoted by both the government and car manufacturers such as legislatively prohibiting the use of wireless devices and disabling some of the amusement features (i.e., Bluetooth setting) during driving. However, driving is a complex task and requires a combination of cognitive engagement and physical operations, which makes it very hard for a driver to concentrate, especially during long trips such as those for truck drivers.

As a promising safety enhancement, in-vehicle sensing has been gaining an increasing attraction since it can continuously monitor the driver's status, from which the advanced driving assistant system (ADAS) can predict human error and thus react timely to prevent accidents from happening. In addition, it can also provide other useful real-time information about the interior of a vehicle, e.g. passenger status, or when a vehicle is parked.

Significant efforts have been devoted to in-vehicle sensing, which, according to the application scenarios, can be classified into five categories, i.e., occupancy detection, fatigue/drowsiness detection, distraction detection, driver authentication and vital sign monitoring.

Occupancy detection [7]–[13] mainly aims to detect, localize, classify the seat occupancy states and then remind the driver before he/she leaves the vehicle. A particular case is the child presence detection (CPD) to prevent a child from being left alone in a closed vehicle, which may cause fatal damage or even death due to heatstroke [14], [15]. Existing studies about occupancy detection can be categorized into four groups according to the adopted techniques, including sensor-based [7]–[13], WiFi-based [16]–[18], image-based [19]–[21], and radar-based [22]–[28] methods.

Fatigue/drowsiness can lead to slow reactions of a driver to the surrounding changes and has caused more than 20% of the reported accidents [29]–[31]. By enabling fatigue/drowsiness detection in the ADAS system, fewer traffic accidents can be expected, and safety and transportation efficiency can be improved. Based on the features extracted, research about fatigue detection can be roughly grouped into three types, i.e., 1) using biological signals such as electrocardiography (ECG) [32]–[48], electroencephalography (EEG) [49]–[66], electromyography (EMG) [67]–[76], 2) using facial contexts such as movement of the face [77]–[96], eye [97]–[110], etc., and 3) joint sensing of facial expressions and body/arm/leg/head motions [111]–[128].

Compared to fatigue/drowsiness, distraction can only be roughly defined since *any activity that takes a driver's attention from the driving task can cause distraction* [129] such as talking to passengers, using mobile phones, etc. As there are so many factors that may cause driver's distraction, the existing research on distraction detection mainly focuses on analyzing the driver's behaviors/activities when operating the vehicle such as acceleration/braking, and mainly contains three different groups including joint sensing of human and vehicle status [129]–[135], human sensing only [136]–[145], and cognitive sensing [146]–[148] which monitors the emotion of the driver to decipher whether he/she is focusing on driving or not.

Driver authentication [149]–[152] can help to improve vehicle security and user experience by automatically adjusting settings of the heating, ventilation, and air conditioning (HVAC), seats, and entertainment. Most of the current research in this area focuses on determining a driver's identity by jointly considering the driving behaviors and biological signals.

Driver vital sign monitoring can assist in preventing accidents caused by unpredictable sudden health deterioration of the driver as well as other in-vehicle sensing applications such as emotion sensing. Most of the conventional vital sign monitoring systems [153]–[158] require a user to wear a lot of sensor pads such as ECG/EEG, which may distract driving and thus are not applicable for driver's vital sign monitoring. Recent advances in wireless sensing techniques [159]–[163] have made contactless vital sensing possible and thus shed light on the future of driver's vital sign monitoring.

The rest of the paper is organized as follows. The abbreviations used in this paper are summarized in Table I for easy reference. Section II reviews the research about occupancy detection and Section III reviews the existing works about fatigue detection. Then, Section IV summarizes the existing methods for distraction detection followed by an overview of driver authentication and vital sign monitoring in Section V. Finally, Section VI discusses the limitations and future works while Section VII concludes this paper.

II. OCCUPANCY DETECTION

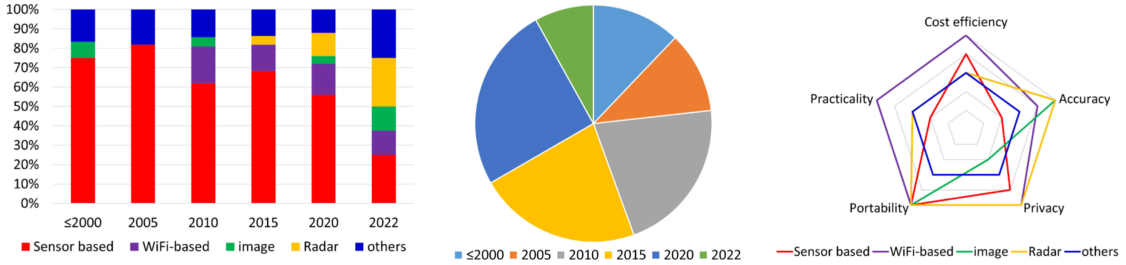
In-vehicle occupancy detection, which detects how many seats of a car are occupied and what object (e.g., an adults/kid/pet/inanimate item) is located at a particular seat has been a key component to enhance driving safety by the Society of Automotive Engineers (SAE) [164]. For example, knowing which seat is occupied by a passenger can be utilized to: 1) remind the passengers who are not wearing seat belts since buckling up can help to reduce the risk of fatal injuries by 45% and moderate to critical injuries by 50% [165]; 2) trigger the emergency system such as airbags in case of accidents to save lives. More importantly, leaving children, especially those who are less than 6 years old and have little ability to exit the vehicle on his/her own, alone in an unattended vehicle can cause very serious damages to organs/brain or even deaths due to heatstroke [14], [15]. As a result, enabling child presence detection has been proposed as a standard feature on the road map of the European New Car Assessment Programme (NCAP) [159], [166] to alert caregivers or emergency services if a child is left alone. Towards this end, many efforts have been devoted to developing accurate and practical occupancy detection systems. Fig. 1 summarizes the existing research about occupancy detection, which, according to the technologies adopted, are categorized into four classes as will be detailed next.

A. SENSOR-BASED OCCUPANCY DETECTION

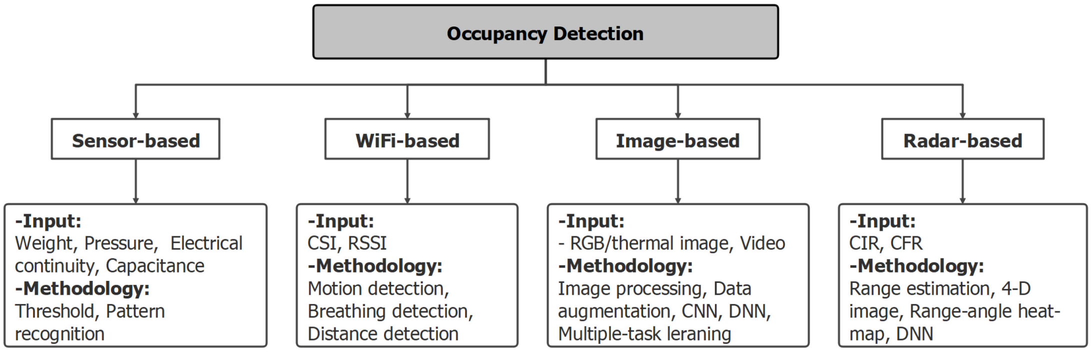
As shown in Table II, sensor-based occupancy detection methods [7]–[13], usually leverage different kinds of physical sensors such as weight, heat, force, capacitance, Radio frequency identification (RFID) to capture the weight, pressure, temperature, electrical continuity, capacitance, etc. elicited by the presence of passengers and then perform further occupancy analysis. This kind of methods is usually very easy to design, manufacture and deploy with affordable cost to most of Original Equipment Manufacturer (OEM) and customers. However, there are three main drawbacks of this kind of methods. First, as the equipment/sensor positions are usually pre-designed and thus fixed, they tend to suffer from very limited coverage within/next to the seats in the car. Second, it is very challenging to find a universal threshold suitable for different cars and human beings. For example, it takes different thresholds to detect the presence of people with different weights. Otherwise, it causes high false positive rate (FPR) if the threshold is too small while high false negative rate (FNR) if the threshold is too large. Third, most of them

TABLE I Mapping of Abbreviations

Abbreviation	Meaning	Abbreviation	Meaning
AAA	American Automobile Association	IR	Infrared
ADAS	Advanced driving assistant systems	ISED	Innovation, Science and Economic Development
AFLW	Annotated facial landmarks in the wild	KNN	K-nearest neighbor
AR	Autoregressive	KSS	Karolinska sleepiness scale
CAN	Controller area network	LGO	Localized gradient orientation
CFO	Channel frequency offset	LRCN	Long-term recurrent convolutional network
CFR	Channel frequency response	LSTM	Long-short-term-memory
CIR	Channel impulse response	MB-LBP	Multi block local binary patterns
COTS	Commercial off-the-shelf	MDF	Median frequency
CPD	Child presence detection	MFV	Mouth feature vector
CPAM	Coordinate pair angle method	MIMO	Multiple-input and multiple-output
CNN	Convolutional neural network	MiRA	Minimum required attention
CSI	Channel state information	MNF	Mean frequency
DAQ	Data acquisition	NCAP	New Car Assessment Programme
DNN	Deep neural network	OEM	Original equipment manufacturer
EAR	Eye aspect ratio	OBD	On-board diagnostic
ECG	Electrocardiography	PCA	Principal component analysis
EEG	Electroencephalography	PERCLOS	Percentage of eyelid closure
EMG	Electromyography	PIR	Passive infrared sensor
EM	Electromagnetic	PLL	Phase-locked loops
EFV	Eye feature vector	PPG	Photoplethysmograph
EMD	Empirical mode decomposition	RF	Radio frequency
ESM	Eye screening mechanism	RGB	Red green blue
EVB	Evaluation board	RFID	Radio frequency identification
FCC	Federal Communications Commission	RMS	Root mean square
FastICA	Fast independent component analysis	RPs	Recurrence plots
FIR	Finite impulse response	RPM	Respiration-per-minute
FIS	Fuzzy inference system	RSSI	Received signal strength indicator
FLIR	Forward-looking infrared	SAE	Society of automotive engineers
FMCW	Frequency modulated continuous wave	SFO	Sampling frequency offset
FOM	Frequency of mouth	SOC	System on chip
FOV	Field of view	STO	Symbol timing offset
FPR	False positive rate	SVDD	Support vector domain description
FNR	False negative rate	SVIRO	Synthetic dataset for vehicle interior rear seat occupancy
GSR	Galvanic skin response	SVM	Support vector machine
HF	High frequency	SVMPPM	SVM-based posterior probabilistic model
HPE	Head pose estimator	SVRs	Support vector regressors
HRV	Heart rate variability	UWB	Ultra wide band
HVAC	Heating, ventilation, and air conditioning	WM	Weighted mean
IBI	Inter-beat-interval	WPT	Wavelet packet transform
IIR	Infinite impulse response	WSD	Weighted standard deviation
LOS	Line of sight	YOLO	You only look once



(a) Distribution of different categories. (b) Overall contribution. (c) Comparison of different methods.



(d) Overview of the existing work.

FIGURE 1. Related works of in-vehicle occupancy detection. (The data is obtained by searching on Google Scholar with the combinations of key words: occupancy car, occupancy vehicle, occupancy automotive, child presence car, child occupancy, and seat occupancy. We review the top 600 related papers and patents, from which we find a total of 99 ones that directly study the topic of in-vehicle occupancy detection. Accessed Mar. 06, 2022.).

TABLE II Sensor-Based Occupancy Detection

Reference	Devices & Input	Methodology	Results & Advantages	Limitations
[7], [8]	Pressure sensor on the seat	Compare the object weight with a threshold	-Easy to deploy -Fast response	-Limited coverage on the seat -Unable to distinguish human from inanimate items
[13]	Pressure sensor on the buckle	Compare the forced pressure with a threshold	-Easy to implement -Fast response	-Limited coverage -Unable to work if a passenger forgets to fasten the belt
[167]	Temperature sensor inside the car	Compare the measured temperature with a threshold	-Easy to deploy -Low cost	-Performance varies in different weather conditions -Ad-hoc temperature thresholds
[10]–[12]	Capacitance sensor embedded in the seat	Measure and analyze the variation trend/pattern of capacitance	-Easy to design -Fast response -Low cost	-Performance varies from person to person due to body differences
[9]	Radio frequency identification (RFID) tag	Detect the electrical continuity within the passenger seat	-Easy to manufacture -Fast response	-Limited coverage within the passenger seat -Lack of universal criteria
[168]–[170]	Passive infrared (PIR) sensor inside the car	Measure the interior motion information such as intensity and direction	-Easy to deploy -Low cost	-Covering line of sight (LOS) with respect to the PIR sensor -Vulnerable to surrounding temperature

lack the ability to distinguish human from inanimate objects. For example, weight-based approaches cannot tell apart a box from a human as long as they are of the same weight.

B. WIFI-BASED OCCUPANCY DETECTION

As more vehicles are being equipped with WiFi transceivers [171]–[173], WiFi-based occupancy detection approaches [16]–[18] are becoming popular due to their superiority in cost and coverage as shown in Table III. The principle behind WiFi-based occupancy detection is that the presence or activity of a human being inside a car can affect the WiFi signal propagation between a transmitter and a receiver, which is embedded in the channel state information (CSI) measurements and can be extracted by a dedicated algorithm. For example, Zeng *et al.* [17] proposed an approach based on statistical electromagnetic (EM) modeling, which can achieve over 96.4% detection rate with less than 3.96% false alarm and a responsive time $\leq$ 20s based on the tests over 5 real babies. [18] presented a portable CPD solution that can work on both 2.4 and 5 GHz commercial off-the-shelf (COTS) WiFi equipment by detecting biological movements at $1-6$mm level. While WiFi-based solutions

TABLE III WiFi-Based Occupancy Detection

Reference	Devices & Input	Methodology	Results & Advantages	Limitations
[17]	Commercial WiFi transceiver embedded in a closed car	Detect motion and breathing of human using smart AI algorithms	-Easy to deploy -Response quickly -Low cost	-Moderate FPR for out-car motions -May miss breathing estimations thus causing miss detection
[18]	Commercial WiFi transceiver	Detect biological movement such as chest movement	-Protect user privacy -No blind-spot -Hot spot integration	-Requires about 1 minute delay -Public test results are not available due to commercial privacy

TABLE IV Image-Based Occupancy Detection

Reference	Devices & Input	Methodology	Results & Advantages	Limitations
[19]–[21], [176]	Two video cameras installed in the first and second row	-Video recording -Laplacian formula for edge detection -OpenCV for motion	Easy to perform	-Call for dedicated camera -Susceptible to illumination changes -May have privacy issue -Not accurate enough
[177]	FLIR[1] One Pro thermal camera under the rear-view mirror	-Image capture -Data augmentation -Multiple-task CNN	-Protect the anonymity of passenger identities -Low power consumption	-Call for dedicated camera -May need training for different cars -Lack of generalization ability
[164]	Synthetic Dataset for Identification[2] of Occupancy	-Image split for training -Pre-train the network[3] -Multiple-task learning	-Decision process is clear to end-user by using statistical metrics	-Only tested on 10 vehicles -Not accurate enough with overall 79.87% accuracy

[1]Forward-looking infrared (FLIR)
[2]Public dataset in [178]
[3]Including ResNet152V2 [179], DenseNet121 [180] and EfficientNetB0-B5-B7 [181] architectures for feature extraction

enjoy low-cost and good coverage, they may suffer from distortions due to the activities outside a car such as cars passing by, since WiFi signals can penetrate the car exterior under certain conditions. Besides, other factors [174] such as channel frequency offset (CFO), sampling frequency offset (SFO), symbol timing offset (STO), and jitters of the phase-locked loops (PLLs) [175] may reduce the CSI quality and thus degrade the robustness of WiFi-based solutions.

C. IMAGE-BASED OCCUPANCY DETECTION

To accurately estimate how many seats are occupied and further localize and recognize the objects,[1] image-based approaches are extensively studied [19]–[21], [164], [176], [177] because an image can provide more visible information such as the contour/edge of an object than WiFi signals. By leveraging techniques such as edge detection [19]–[21], and learning including convolutional neural network (CNN), multi-task learning [164], which can automatically identify object-related features for recognition, great performance can be achieved. However, as shown in Table IV, capturing high-quality images requires dedicated cameras and it takes efforts to construct a *good* dataset to train the network, especially for manual data labeling and annotation. For better privacy protection, thermal images [177] are captured and then fed into a CCN network based on multi-task learning technique. The work in [164] designed a CNN network which is pre-trained from the existing CNN models including ResNet152V2 [179], DenseNet121 [180], and the most recent EfficientNetB0-B5-B7 [181]. The system yields about 79.87% accuracy on the public synthetic dataset for vehicle interior rear seat occupancy (SVIRO) [178] to classify people and inanimate objects over 10 different vehicle interiors and 25,000 scenarios. As seen, the accuracy is limited because different vehicles have different background information which challenges the classifier greatly.

D. RADAR-BASED OCCUPANCY DETECTION

Recently, the unprecedented development of radar techniques [182]–[187], especially millimeter-wave (mmWave) radar has offered new opportunities for occupancy detection, classification and localization since mmWave can provide better directionality, angular, angular, and range resolution due to its high frequency and large bandwidth. As shown in Table V, recent years have witnessed the blossom of mmWave-based occupancy detection systems [22]–[28]. For example, Vayyar [22] presents occupancy detection and classification by estimating the 4D image of the object. Texas Instrument [27] demonstrates the feasibility of occupancy detection using 77 GHz frequency modulated continuous wave (FMCW) radar to construct the range-angle heatmap of the object.

Another major superiority of the mmWave system is that it is easy to be integrated on a single chip [23], [24] or a small unit [26], offering flexibility in device locations and better portability. At present, Federal Communications Commission (FCC) has been trying to enable State-of-the-Art Radar Sensors in 60 GHz Band *to increase the practicality of using mobile radar devices in the 60 GHz band to perform*

[1]Few of the WiFi-based approaches can localize and identify an object occupying a seat as the time and space resolution of COTS WiFi is limited by the bandwidth (20MHz-80 MHz) and the number of antennas (≤ 3 usually).

TABLE V Radar-Based Occupancy Detection

Reference	Devices & Input	Methodology	Results & Advantages	Limitations
[22]	Radar-on-chip 60GHz and 79GHz	-MIMO[1] radar -4D mmImage -Occupant classification	-High resolution -Accurate -Single-chip	-Extra hardware needed -Work in LOS condition -Complexity is hard to tell
[23]	MIMO Radar 60 GHz, FMCW	Breathing movements detection	-Seat position -Object recognition	-Extra cost -Results for awake/in-motion child are not mentioned yet
[24]	Radar EVB[2] 60GHz	-Remind the driver when the door is closed -2D camera	-Occupant classification and positioning -Chipset solution	-May need multiple radar sets -Multiple-sensor fusion may require high computational costs
[26]	Radar on 60-64 GHz	Radar techniques	-Approved by FCC -First sensor supplier	-To be evaluated by the market -Method not available yet
[27]	FMCW radar 77GHz	Range-angle heatmap	-Accurate within FOV[3] -Location of the object	-Only works for FOV in $\pm 60^\circ$ -Practical validation is not presented
[28]	UWB[4] radar	-Spatial/time features -2D convolutions -MaskMIMO	-94.6% accuracy -Lightweight -Smooth realtime run	-8 nodes distributed in the car -Need more testing scenarios[5] -Tests on practical human needed

[1]Multiple-input and multiple-output (MIMO)
[2]Evaluation board (EVB)
[3]Field of view (FOV)
[4]Ultra-wideband (UWB)
[5]Only testing results in the garage and outdoor parking lots are provided. More tests such as street parking are needed since passing-by cars may cause interference on the received signal and thus degrade the performance.

innovative and life-saving functions, including gesture control, detection of unattended children in vehicles [188], which provides legislative support and incentives for mmWave-based occupancy detection approaches. Companies such as Innosent [23], Infineon [24] and NOVELIC [25] have announced their system-on-chip (SOC) solution of presence detection. In February 2021, IEE VitaSens [26] launched VitaSense [189], *an interior radar sensing solution for CPD in vehicles*, with grant from North America and Science and Innovation, Science and Economic Development (ISED) of Canada [190], [191]. While mmWave is very encouraging, it is yet to be integrated with the current in-car system (most on 2.4 GHz and 5 GHz) without additional hardware cost.

III. DRIVER FATIGUE DETECTION

Fatigue, which degrades perception, delays reaction, and impacts judgment of a driver on his/her surroundings, has been shown as a prime culprit for over 20% of car accidents [4]. What is worse is that drivers are more prone to feeling fatigue or drowsy nowadays since the roads are becoming more crowded due to the rapid increase of motor vehicles [29] and thus the drivers have to be more focused. It is imperative to seek effective solutions for fatigue detection and prediction so that *smart cars* can sense the status of the driver and respond accordingly, such as sounding a warning/alarm message with an audio assistant system. To meet the demand, various research and commercial solutions have been proposed as summarized in Fig. 2.

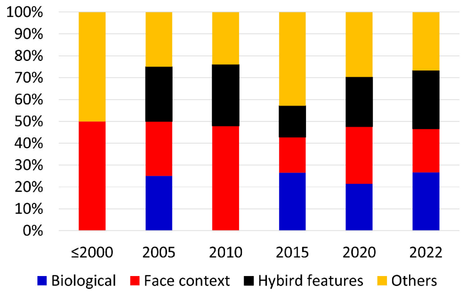
A. FATIGUE DETECTION USING BIOLOGICAL SIGNALS

By directly measuring the variation of biological response related to the human neural system, biological signal-based (e.g., EEG [49]–[66], ECG [32]–[48], and EMG [67]–[76]) fatigue detection has been viewed as the golden standard, and the related works are summarized in Table VI and Table VII. In most of these approaches, users are asked to wear a number of electrode pads for data collection. Then, pre-processing techniques such as Finite Impulse Response (FIR) filter, Infinite Impulse Response (IIR) filter [34], Principal component analysis (PCA) [59], empirical mode decomposition (EMD) [192] and fast independent component analysis (FastICA) [34] are adopted, which aim at removing the noise and artifacts while retaining the signal components within a certain range of frequency. Afterwards, the cleaned signal is fed into some feature extraction module to get the fatigue-related features such as α and β information, inter-beat-interval (IBI), spatial spectrum, temporal dependency, variation, kurtosis of the power spectrum etc. To get the fatigue information, most of the existing works tend to formulate the problem as a discrete classification problem, such as support vector machine (SVM), deep neural network (DNN), K-nearest neighbor (KNN). It is worth to note that the discrete classification model is very straightforward by feeding the data into the well-studied classification models, which can usually achieve reasonably good performance. However, the manual labeling process of fatigue can be error-prone, since the evaluation is subjective and even the most experienced biological experts may get confused in distinguishing fatigue and normal status. For this reason, decision making-based on Fuzzy Inference System (FIS) [195]–[197] have been studied in assisting driver's fatigue detection since it is hard to quantify human's neuron response even for the same activity. Another main drawback of fatigue detection using biological signals is the requirement of many wearable sensors, which may distract the driver. Less intrusive sensors are being considered before such methods can be widely accepted by the market.

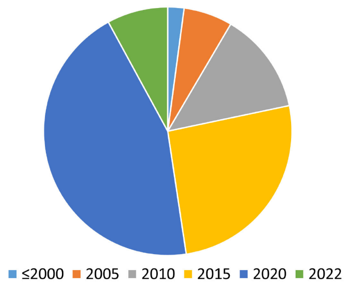
TABLE VI Biological Signal-Based Fatigue Detection-Part I

Reference	Devices & Input	Methodology	Results & Advantages	Limitations
[52]	Smartwatch with bluetooth for EEG signal acquisition	Support vector machine-based posterior probabilistic model (SVMPPM)	-91.92% detection accuracy -83.78% early detection -Evaluate by headband as the ground truth	-Wearable devices are needed -Only evaluated on simulated driving experiments
[53]	EEG sensor	-α and β information extraction -Normalized Haar WPT[1]	Only single-channel EEG signal is needed	-User has to have physical contact with EEG sensor -Tested on public database
[54]	EEG sensor	-Hierarchical clustering to assess the subject variability -Subject-transfer framework	-Greatly reduced the calibration for about 90% -Robust over different users	Only the data from a simulated driving task is used for validation
[55]	Neuroscan EEG system with 40 electrodes covering the head area	-Temporal dependencies extraction -Spatial features fusion -Spatial–temporal CNN	-97.37% detection accuracy -High computational efficiency and low delay	Only laboratory and simulated driving data are captured for validation
[56]	EEG sensor attached on the head area	Enrich the EEG data with the intensity of head-movements	-Low-power consumption -On-chip feature extraction	6 subjects in one hour monotonous simulated driving experiment
[57]	EEG sensor attached on the head area	-Feature weighting to learn the importance of different features -Episodic training for domain generalization	Subject adaptive with no need for calibration	Details of experiment setup is not available
[58]	EEG sensor attached on the head area	-Fused multiple entropies -Autoregressive (AR) model -Channel selection	-Leave-one-out cross-validation -98.3% detection accuracy	Data is captured from 12 healthy subjects on simulated driving experiments
[59]	EEG sensor attached on the head area	Principal component analysis (PCA)+DNN[2]	95% detection accuracy	6 healthy volunteers in a simulated driving experiment.
[32]	ECG sensor	-Genetic algorithm and support vector machine (SVM) -Mercer kernel	-97.01% detection accuracy -Average delay of 0.55ms	Details of experiment and data acquisition are not available
[33]	Collecting ECG signal using DIY[3] device	-HRV[4] characteristics -Power spectrum ratio $\beta/(\theta+\alpha)$ -Sample entropy	-No need for patch electrodes -Realtime implementation -High integration	Experiment was performed in simulated driving conditions
[34]	-ECG electrode placed on wrist -Camera for ground truth -Manually labeling	-FIR and IIR[5] filters to remove the effect of noise and artifact -FastICA[6] to estimate the independent components -SVM and KNN[7]	-Two-class detection provides better accuracy than 5 states[8] -$\geq$ 93.1% classification accuracy	-Simulated driving data is collected only -Intrusive data collection which may distract the driver
[35]	-Wearable ECG and PPG[9] sensors -Polar H7 strap and a PPG sensor	-Recurrence plots (RPs) generated from the R–R intervals (RRIs) of heartbeats as features of CNN	Overcome interference from the slight movement of subjects on data acquisition	Only data collection from a virtual driving environment
[36]	-Infrared (IR) camera -LAB DAQ[10]device -ECG sensor with Ag–AgCl electrodes	-Higher order spectral feature -Linear discriminant analysis -Quadratic discriminant analysis	Overall maximum accuracy of 96.75%	Driving monotonously on a driving simulator at a limited speed for long hours to simulate fatigue
[67]	EMG, GSR[11]and bluetooth for data acquisition	Variations of EMGs in frequency-domain	-92% detection accuracy -KSS[12]for ground truth labeling	No practical measurement is available
[68]	Surface EMG signal from upper arm and shoulder	-Five features including range, variance, spectral power and kurtosis, and shape factor are fed to a KNN classifier	90% detection accuracy over 13 testers	Driving simulator on a monotonous route

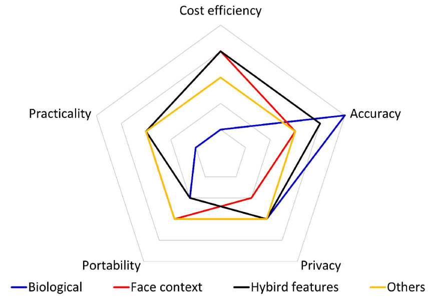
[1] Wavelet packet transform (WPT)
[2] Deep neural network (DNN)
[3] Do it yourself (DIY)
[4] Heart rate variability (HRV)
[5] Finite Impulse Response (FIR), Infnite Impulse Response (IIR)
[6] Fast independent component analysis (FastICA)
[7] K-nearest neighborhood (KNN)
[8] Normal, drowsy, fatigue, visual and cognitive inattention
[9] Photoplethysmograph (PPG)
[10] Data acquisition (DAQ)
[11] Galvanic skin response (GSR)
[12] Karolinska sleepiness scale (KSS)



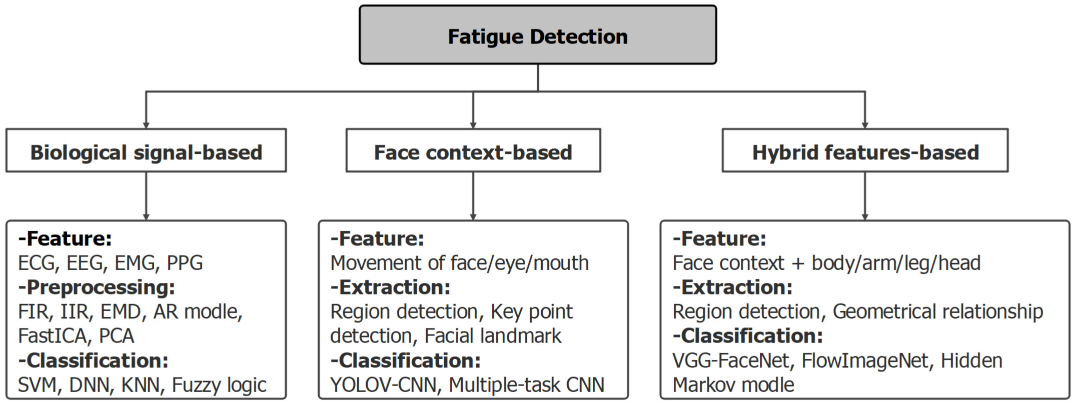
(a) Distribution of different categories.



(b) Overall contribution.



(c) Comparison of different methods.



(d) Overview of the existing work.

FIGURE 2. Related works of in-vehicle fatigue detection. (The data is obtained by searching on Google Scholar with the combinations of key words: driver fatigue, driver drowsiness, vehicle fatigue, vehicle drowsiness, automotive fatigue, and automotive drowsiness. We review the top 600 related papers and patents, from which we find a total of 189 ones that directly study the topic of in-vehicle fatigue detection. Accessed Mar. 11, 2022.).

TABLE VII Biological Signal-Based Fatigue Detection-Part II

Reference	Devices	Methodology	Results & Advantages	Limitations
[69]	DIY EMG data collection system with electrode on the surface of cloth with thickness $\leq$2mm	-Special design of amplifier -FastICA and digital filter -Kolmogorov Smirnov Z analysis -Mahalanobis distance	Noncontact data acquisition from biceps femoris	Driving simulator on a monotonous route
[70]	EMG sensor collecting data during driving a truck	Mean frequency (MNF), median frequency (MDF), and the signal RMS[1] amplitude	10 healthy volunteers	Physical contact with users
[192]	Non-contact EMG sensors located in a cushion on the driver's seat	-FastICA, denoise by EMD[2] -PCA and multiple linear regression study linear relation among features	-12 healthy males -Model based -91% detection accuracy from 13 testers	Simulated driving experiments
[193]	-Wearable chest-strip with sensor -HRV estimation	The weighted mean (WM) and the weighted standard deviation (WSD) of the high frequency (HF) band in the power spectrum	Results of SVM, random forest and KNN are demonstrated	-Virtual driving environment -Physical contact with user for data collection which may distract the driver
[51]	ECG, EEG and PSG[3] sensor are used for HRV and ground truth data collection	-Eight HRV features are monitored -Multivariate statistical process control	-92.3% detection accuracy over 34 testers -1.7 times false alarm per hour	-Data collected in a virtual vehicle simulator -Physical contact needed for data collection
[194]	-Cheststrap -Wrist watch	Multi-layer artificial neural network and SVM	91.3% detection accuracy	Wearable sensors

[1] Root mean square (RMS)
[2] Empirical mode decomposition (EMD)
[3] Polysomnography (PSG)

TABLE VIII Fatigue Detection Using Independent Facial Features

Reference	Devices & Input	Methodology	Results & Advantages	Limitations
[77]	-Camera for self-built data set -Public data set WIDER FACE	-Improved YOLOV3-CNN for facial region detection -Eye feature vector(EFV) and mouth feature vector(MFV)	-Detect the fatigue state at a speed of over 20fps with 95.10% accuracy -50 test drivers	Simulated driving experiments
[78]	-National Tsing Hua University Driver Drowsiness Detection (NTHUDDD) dataset -Video clips for labeling	-Multiple-task cascaded CNN -Static features extraction from a partial facial image -Dynamic features extraction from a partial facial optical flow -Two-stream neural network	An accuracy of 97.06% over 36 subjects of different ethnicities on a public dataset	-Practical validation is not provided yet -Privacy concern, which is common for all image based methods
[79]	-57 normal videos, 94 slightly fatigued videos and 49 severely fatigued videos.	-Face key point detection -Multi block local binary patterns (MB-LBP) -Adaboost classifier -Fuzzy inference system	-$\geq$ 94.7% accuracy -Detection speed is 53 frames/s	When the driver wears glasses or the face rotates at a large angle, the accuracy of the algorithm decreases
[80]	YawDD dataset [88] and self-built dataset with 10 volunteers	-Multiple-task CNN for face detection -DLIB[1] to localize the key points of face -LSTM[2] for classification	-$\geq$ 93% accuracy -Reduce half of the running time than DLIB	-The detection performance under insufficient light still degrades -System vulnerable to light conditions
[81]	-Extended Cohn-Kanade dataset -Psychological image at stirling dataset	-Facial landmarks -OpenCV for image processing -DLIB for feature extraction	82.79% detection accuracy	No practical validation is provided
[97]	-CEW Database -ZJU Database -BUAA Eye Database	-Dual-stream bidirectional CNN -Eye gaze pattern analysis -Eye screening mechanism (ESM) to eliminate the detected errors	Improves about 2.9% in the average accuracy compared with using CNN alone	No practical validation is provided
[98]	-Infrared videos for self-built data base -ZJU Database	-CNN for eye state detection -PERCLOS and blink frequency	Robust for wearing glasses	Need active infrared light (850nm) to fill light illumination
[99]	Raspberry Pi 4	Eye aspect ratio (EAR) technique	-90% detection accuracy -Under initial, wearing spectacles, dim light and microsleep condition	Not tested over enough number of subjects
[100]	Head-mounted eye-tracking camera	Fuzzy KNN	Reach to about 89% accuracy in average	Highway-driving simulator experiment
[101]	-Dome camera installed on the bus -23 testers under different lighting conditions	-Eye openness detection using spectral regression -Adaptive integration to estimate eye state	Explore the case when a camera is in an oblique view w.r.t. the driver's face	Validation is on simulated bus driving videos

[1]DLIB:an open-source software library
[2]Long-short-term-memory (LSTM)

B. FATIGUE DETECTION USING INDEPENDENT FACIAL FEATURES

Without requiring wearable sensors, image/video-based fatigue detection using facial features has become popular, such as those based on face recognition [77]–[96], eye detection [97]–[110], and the combination of the features extracted from face, eye, mouth, etc. In most of these approaches, a face/eye/mouth region detection module is firstly designed to refine the input image to remove redundant information outside the region of interest. As shown in Table VIII, region recognition methods include you only look once (YOLOv-CNN) [198], multi-task cascaded CNN, DLIB keypoint detection [199], etc. The next step following the region detection is to extract the fatigue-related visible features such as eye open/close/gaze, mouth open/close, face being twisted or not. Afterwards, the joint analysis of the extracted features is performed. For example, the percentage of eyelid closure over the pupil over time (PERCLOS) of a driver larger than 80% [200] is a strong indication that he/she is drowsy, even though the specific threshold/percentage may vary from person to person and at different time over a day. In this case, by continuous monitoring, if the system further detects that the driver yawns more frequently than usual, there is a high probability that he/she is sleepy and thus an alert can be triggered. In the last, different strategies can be adopted such as Two-stream neural network, Adaboost classifier, Fuzzy inference fusion, and long-short-term-memory (LSTM) network to output the final decision.

While many related works have been proposed with their own advantages and drawbacks, as shown in Table VIII, they share several common limitations: 1) Putting a camera in front of the driver during driving may not only induce **privacy concern** but also distract the driver and thus increase the risk of accidents; 2) Many of the related works are studied on **public datasets** such as WIDER FACE [77], National Tsing Hua University Driver Drowsiness Detection (NTHUDDD) dataset [78], [112], [201], YawDD dataset [88], CEW Database [97], ZJU Database [97], BUAA Eye Database [97], most of which are collected in a laboratory environment when the driver is driving on a simulator. As a result, it is really hard to conclude about the practical performance since human beings tend to have very different biological reactions in practical driving. To expedite the real-world application, efforts are still needed on developing highly efficient data collection tools on practical driving for further validation; 3) Most of the existing studies are based on the dataset when users **face right towards the camera**, while few of them have discussed the case if a user faces towards the camera with an oblique angle, since driving can involve frequent activities requiring head turns, such as checking the rear-mirror, looking at the side mirrors before lane changes, etc.

C. FATIGUE DETECTION USING HYBRID ANALYSIS

As aforementioned, to capture high-quality images/videos so that minute facial/eye/mouth changes can be extracted, dedicated cameras are needed. In addition, under some circumstances, a strict installation angle/position is required to make sure that the camera and user's face are facing towards each other. However, a driver has to keep checking the surrounding environment during practical driving, the relative position/angle between the camera and the driver's face is time variant, and it is impractical to assume that frontal images are always available. To tackle this issue, some of the existing works have explored solutions by studying how the big motion of a driver, such as head movement due to nod, arm/hand motion when moving their hands away from the steering wheel unintentionally, can assist the fatigue detection, because sensing big motions is always feasible during driving. Although relying on sensing the big motion itself may not be accurate enough for reliable fatigue detection as such big motions can also happen when the driver is sober, they can provide good auxiliary information.

Towards this end, many research works [111]–[128] have been proposed by jointly analyzing the big motions and the imperceptible changes corresponding to the subtle motion of face/eye/mouth as shown in Table IX. For example, Part *et al.* [111] presented a joint analysis on local facial expression and head gesture using VGG-FaceNet and FlowImageNet architecture, respectively. The results show that joint features including both face and head can contribute about the 5% improvement in drowsiness detection accuracy over the public NTHUDDD video dataset [112], which are collected over 36 subjects including different genders and ethnicities. While [111] is evaluated on a public dataset collected under simulated driving conditions, Mittal *et al.* [113] develops a fatigue detection system that combines the information from head pose (with a particle-filter based 3D model to track head motion), lip and eyes, which is then comprehensively evaluated with 14 subjects driving a car on different round-trip routes through the University of California campus at different times, including morning, afternoon, dusk, and night. Further studies also involve the head pose dynamics [114], [115], [202], head orientation and arm position [116], [117], which improve the fatigue detection accuracy by 2% - 10%, compared to the benchmark methods using only facial features. To further handle the time-variant relative position between the camera and a driver's face, multiple cameras can be distributed around the car for data acquisition [114], [115], [202]. Although the fatigue detection accuracy is improved, many new practical problems arise as well, such as the cost of hardware, deployment, computational complexity, and more importantly how to fuse the information from multiple cameras while satisfying the real-time detection requirement.

IV. DRIVER DISTRACTION DETECTION

Driver distraction, which can increase the risk of accidents, may be caused by many factors. As introduced in Section I, there exists no universal definition for distraction during driving [205]–[207], and a widely accepted concept is that, *any activity that takes a driver's attention from driving belongs to the cause of distraction* [129] such as talking to passengers, using mobile phones, under different kinds of negative emotions including anger [208], anxiety [209], sadness [210], etc. As shown in Fig. 3, the community has been exploring how to detect/prohibit distraction in many different directions to improve driving safety. One example is that playing with mobile devices when driving is legislatively prohibited in most countries. Besides, car manufacturers are adding more convenient designs such as integrating switches of phone-call, music-playing, cruise-setting on the steering wheel area so that a driver does not need to move his/her hand off the steering wheel when they have to utilize related functions. Also, some of the amusement features are disabled during driving such as that Tesla [211] stops allowing drivers to play video games during driving. However, there exists a conflict between simplifying the design/functions and satisfying the users. In other words, to make the car more intelligent and improve the driving experience, manufacturers have to develop and integrate more functions (e.g., entertaining, relaxing), which again will increase the chance of distraction. Therefore, an automatic distraction detection system is needed, which can alert a driver, or more intelligently, provide real-time corrections whenever distraction is detected.

A. DISTRACTION DETECTION BASED ON JOINT SENSING OF HUMAN AND VEHICLE

Among the many distraction detection studies [129]–[135], joint sensing of the vehicle and human status is firstly proposed, as shown in Fig. 3 and Table X. Tang *et al.* first [130] presented a driver's distraction system by leveraging the vehicle data (usually including speed, steering angle, position of

TABLE IX Fatigue Detection Using Hybrid Analysis

Reference	Devices & Input	Methodology	Results & Advantages	Limitations
[4]	-YawDD video dataset [204] -NTHUDDD video dataset [203]	-Eye and mouth characteristics -Multiple-task learning -PERCLOS and FOM[1]	98.81% fatigue detection accuracy	-Privacy issue -More practical validation needed
[111]	NTHUDDD video dataset [203]	-Face and head gesture based on FlowImageNet -Facial feature representation based on VGG-FaceNet	-Performance comparison with CNNs and LRCN[2] -Evaluations on NTHUDDD dataset with 36 subjects	No validation on real driving conditions
[113]	-IEEE1394 camera to capture the gray-scale video -Vicon optical motion capture to track the head pose	-AdaBoost, LGO[3] histogram -Support vector regressors (SVRs) -Particle filter to track the 3-D head motion	–Head pose, lip corner, eye -14 subjects driver the LISA-P[4] for experiments -Different round-trip routes at different times	-Near-IR illuminator to ensure the light conditions -Performance degrade when the yaw of head approaches 90°
[114], [115], [202]	Distributed camera framework	-Head pose and dynamics -Facial features + geometric relationships to estimate the head pose using a 3-D model	-Practical on-road driving in urban streets and freeways -Emphasis on events inducing spatially large head movements (e.g., merge and lane change)	-Call for multiple cameras inside the car -Fusion among multiple cameras may increase the complexity in practical applications
[116]	Eye tracking and accelerometer to capture head motion	-Blink rate, yawn motion, head motion -AdaBoost and multi-nomial ridge regression	-Computer game driving -96% and 90% accuracy for within and across subjects -Revealing a counterintuitive observation that drivers yawn less before fall asleep	No practical driving validations
[117]	Kinect active sensor	-Eye behavior + arm position + head orientation + facial expressions -AdaBoost classifier and Hidden Markov model	-Driving simulator over 8 drivers -90% distraction detection accuracy	-Manually labeling is time consuming and error-prone -Practical tests needed

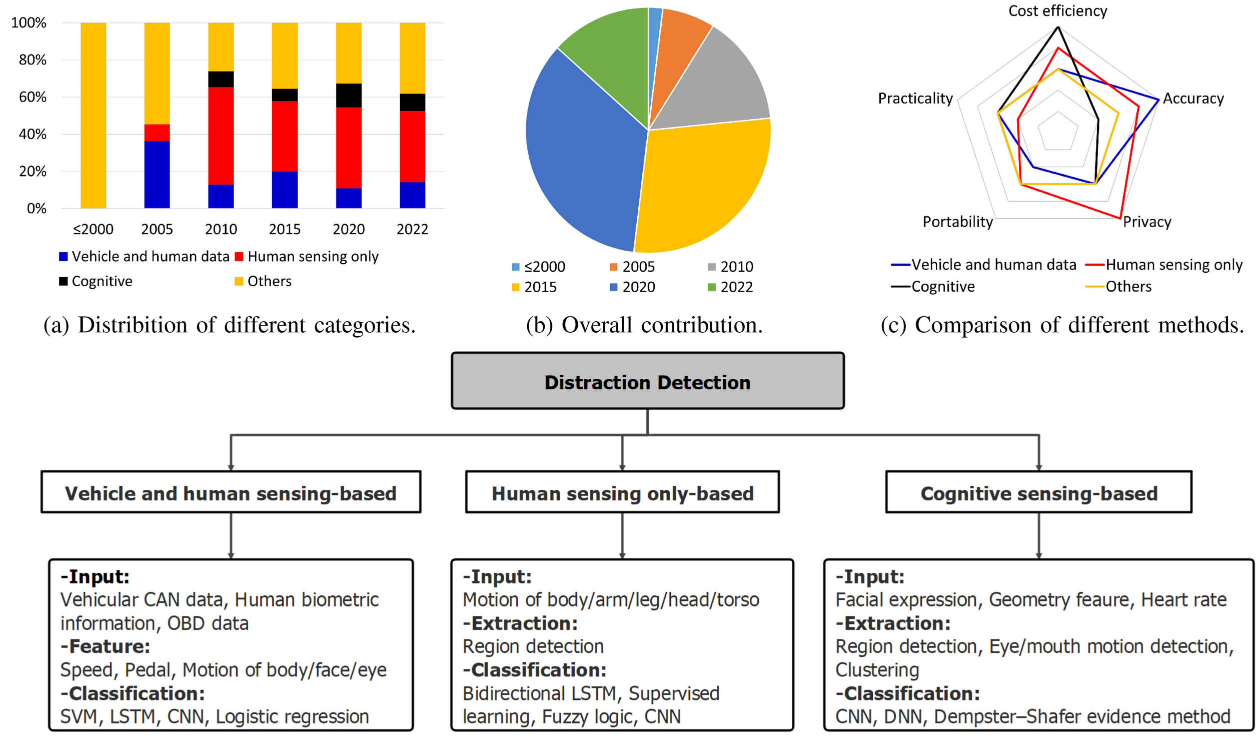
[1]Frequency of mouth (FOM)
[2]Long-term recurrent convolutional network (LRCN)
[3]Localized gradient orientation (LGO)
[4]Laboratory for intelligent and safe automobile (LISA)

the accelerator pedal, the brake pedal, etc.) gathered from the vehicle controller area network (CAN) [204] system, which is then fed into an SVM classifier for distraction detection. Later, motion information which mainly corresponds to the big motion of the human body such as body/leg/arm movements were further involved in [131] and yielded about 90% detection accuracy. To further improve the accuracy, the relationship between the head motion and distraction was studied in [132] and then fused with the vehicle data [134], which also explores the time-domain information by utilizing LSTM-recurrent neural network. The correlation between eye glance and steering movements was analyzed in [212], which verified the feasibility of distinguishing different types of distraction. To test the performance, a real-time system was implemented in [129] and 30 participants were recruited to drive on a straight country road while performing eight pre-defined secondary task (e.g., playing radio, setting the navigation to a destination) on the multimedia interface to evoke distractions. In total, the authors got about 150 minutes distraction data and 50 minutes attentive data, which demonstrates about 96.6% accuracy.

While these works have shown promising results, most of them are evaluated on the data collected from a driving simulator or practical driving but following a simple route. Although many efforts have been made to make the driving simulator more realistic such as involving challenging routes, playing sound around as distractions, experiences from a driving simulator are still different from practical driving [147], and the validations/findings from the aforementioned works may not hold in practice. as shown by the degraded performance during practical driving [129], [134], and it is worthwhile to conduct more real-world data based studies.

B. DISTRACTION DETECTION ON HUMAN SENSING

Instead of joint vehicle and human sensing, distraction can also be detected based on human sensing only. The main reasons are as follows. First, vehicle data is not always available. Second, it is difficult to build a universal vehicle data-based driving profile since driving behavior can be affected by many external factors and a driver may respond differently to the same stimulus. For example, braking frequency on a highway



(a) Distribution of different categories. (b) Overall contribution. (c) Comparison of different methods.

(d) Distribition of different categories in different years.

FIGURE 3. Related works of in-vehicle distraction detection. (The data is obtained by searching on Google Scholar with the combinations of key words: driver distraction, driver inattention, driver behavior, vehicle distraction, vehicle inattention, automotive distraction, and automotive inattention. We review the top 700 related papers and patents, from which we find a total of 168 ones that directly study the topic of in-vehicle distraction detection. Accessed Mar. 15, 2022.).

TABLE X Distraction Detection by Joint Sensing of Vehicle and Human

Reference	Devices & Input	Methodology	Results & Advantages	Limitations
[130]	-Prototype vehicle CAN[1] bus -Dynamic vehicle data	-Non-intrusive and real-time detection -Driving with secondary tasks	Up to 95% detection accuracy	Data is collected by using a static driving simulator
[131]	-Vehicle CAN data -Motion sensor	Focus on perceivable distractions with leg and head movements	-Over 90% detection accuracy -Real-time testing	Testing route is limited
[132]	FaceLAB eye tracker [133]	-Eye and head movements -Laplacian SVM and semi-supervised extreme learning machine	Semi-supervised learning improves about 2.45% using unlabeled data	-Constrained experiment settings with limited driving behaviors -Performance on unsupervised learning needs to further evaluate
[129]	-CAN-Bus data -Head tracking images -150 minutes distracted and 50 minutes attentive data [206]	-Joint use of head and the information of a car itself -Long-range temporal context of driving and head tracking data -LSTM	-Accuracy of up to 96.6% -30 participants (12 female and 18 male, aging from 23 to 59)	-Constrained distracted activities during driving -Performance degrades under complicated driving behaviors -Straight route with moderate traffic density
[134]	-Stereo vision system -Lane position sensor -CAN vehicle sensor	-SVM -Attention mapping algorithm	-12 professional drivers driving Volvo FH 12 truck -Accuracy varies from 10% to 99%	Performance varies a lot due to different relative angles between the camera and driver

[1]Controller area network (CAN) [204]

TABLE XI Distraction Detection by Sensing of Human Only

Reference	Devices & Input	Methodology	Results & Advantages	Limitations
[213]	-Full scale image -AUC[1] Distracted Driver dataset	Bidirectional-LSTM (BiLSTM) Networks	Classification accuracy of 92.7%	Practical data validation is not provided
[214]–[216]	Track and record the duration of looking on or away from the road	Context dependency and the possibility to self-pace from MiRA[2]	A real-time implementation is demonstrated	Driving simulator experiment with 16 bus drivers
[217]	Public database [221] with full scale image inside the car	-Supervised learning -Combination of CNN and random forest	Detection accuracy of 95%	Public database under controlled experiment
[219]	Driving simulator with data acquisition using Matlab simulink platform	-Euclidean distance -Fuzzy logic and fuzzy neural networks	-Driver-in-the-loop experiments -Within 20% estimation error	Practical driving test is not provided
[220]	Self-built dataset based on AUC dataset model	-Encode and decoder -Capsule network -Face and hand detection	90% accuracy with 92% precision score	The routine condition during the experiment is not presented

[1]American University in Cairo (AUC) Distracted Driver Dataset
[2]Minimum Required Attention (MiRA)

and urban roads is different, while driving in snowy weather is different from driving on a sunny day as well. In addition, the measurement error of the CAN system is vehicle-dependent, which again induces new noise in the vehicle-specific dataset.

Distraction detection based on human sensing only can be mainly divided into two categories. Existing works in the first category mainly leverage the visualized big motion (e.g., head pose/orientation [136]–[139]) of the human body or the minor motion involved in the eye movement/glance [140]–[142], facial expression [143]–[145], and etc. For example, Zhao *et al.* [136]–[138] introduced a distraction detection method by utilizing the head pose estimator (HPE _ Resnet50) network structure to extract the head pose/orientation (described in Euler angle) of a driver [136], based on the 300W-LP [221] and Annotated facial landmarks in the wild (AFLW) datasets [222]. A similar idea was proposed in [137], [138], which extracted the head pose using a coordinate-pair-angle-method (CPAM) and then DNN for further classification. Praveen *et al.* [223] demonstrated the feasibility of distraction detection by tracking the face pose using a clustered approach based on Gabor features. The full-scale information of a human body was leveraged by an ensemble of ResNets in [224] to distinguish distraction from images of normal driving, yielding an accuracy of 94.28% on the American University in Cairo (AUC) dataset. On the other hand, Rezaei *et al.* [142] created a cascaded network using Haar-like Masks to detect the subtle eye movement such as opening/closing for distraction recognition, which could detect distraction from both the frontal direction and an oblique angle of a tilted head pose, making a big step towards practical applications. [141], [216], [225] explored metrics such as eye gaze direction [225], blink pattern [141], and on-road/off-road gaze duration [216]. [226]–[228] demonstrated the feasibility of using activities of eyes and mouth, and a review of driver distraction detection using facial expressions was presented in [144], [145]. Note that the different features extracted from subtle eye/face/mouth movements are usually fused [143] and then fed into various classifiers such as AdaBoost, Random Forest, SVM, CNN, DNN for distraction analysis.

Instead of using either the big motion [136]–[139] or minor motion [140]–[145], [226]–[228], the second category [140], [146], [203], [213]–[220], [229]–[231] fuses features from the big motion and minor motion together as shown in Fig. 3 and Table XI. Although different features are extracted, the main steps of this kind of methods can be summarized as follows:

- *Step 1:* Image capturing using dedicated RGB/thermal cameras, which are usually mounted on the windshield/dashboard and pointed towards a driver's face as much as possible while not blocking his/her view.
- *Step 2:* Image pre-processing, such as resizing, noise removal, enhancement, and region detection corresponding to the driver's arms, legs, hands, head, torso, face, mouth, eyes, etc. Note that different region detection methods may be designed for a specific purpose. For example, eye detection takes a smaller window to capture more details while body contour extraction requires full-scale images.
- *Step 3:* Feature extraction, construction, and classification, which are closely related to the cascaded network and the loss/objective function adopted. The two most common feature extraction methods are shape-based (e.g., calculating the *distance* such as Euclid distance using several key points in the image) and appearance-based by leveraging the color, context, or correlations between different images.

C. COGNITIVE DISTRACTION DETECTION

Another type of distraction is cognitive distraction, which is mainly caused by negative emotions of a driver such as anger [208], sadness [210], and anxiety [209]. Since emotion is mainly related to the activity of one's brain and neural system, cognitive distraction is hard to be detected using the aforementioned detection approaches. It is possible that one may have different behaviors under different moods. However, different people have different ways of expressing their emotions, and thus it may not be accurate to judge one's emotion purely based on his/her behavior. In this sense, cognitive distraction is probably the most difficult type of distraction to be detected [146].

Recent work [147] presented a review of the existing research on in-vehicle emotion sensing, which, according to the information adopted to sense emotion, can be divided into biological signal based (e.g., ECG, Heart rate and blood pressure, etc.) [232]–[239], speech signal based [240], [241], facial expression based [242]–[248], behavior based [249], and those using the combination of different features [148]. Biological signals-based methods can achieve good accuracy because those signals are directly related to the physiological response of a human being under different emotions. However, capturing biological signals is usually intrusive and requires physical contact between electrodes and human body, and is not convenient for a practical driving scenario. In addition, biological signals are often very weak and thus highly vulnerable to external distortions such as noise and unavoidable human body motions. Note that Du *et al.* [148] have shown that the joint use of biological features (e.g., heart rate extracted from RGB images) and facial expressions from images can improve the emotion detection accuracy by about 5%, which may shed light on a new direction of cognitive distraction detection.

V. MORE APPLICATIONS OF IN-VEHICLE SENSING

In this section, we introduce two more other in-vehicle sensing applications, especially those wireless sensing-based techniques due to its superiority in cost and coverage.

A. DRIVER AUTHENTICATION

As remote keyless system [250] has become standard equipment for modern vehicles, most of them are still relying on a token matching and rolling scheme, which has been reported for several security concerns [150], [251]–[253]. Therefore, enabling a smart driver authentication system can help to protect a car from improper use without the permission of the driver/owner [150]. Moreover, automatic driver authentication can enable intelligent driver-specific adjustments, such as the seat and mirror positions [149].

Towards this end, the works [150], [151] built a driver identification system by sensing the driving behavior using the data from the in-vehicle CAN system, with SVM and CNN + SVDD (Support Vector Domain Description) classifiers, respectively. Face recognition techniques are leveraged in [152] while [254] utilizes the On-Board Diagnostic (OBD) port for collecting data about speed, pedal movement, fuel flow, etc., which are then fed into a machine learning module for classification. Biometric-based driver authentication methods have also been proposed using different biometric information including palm prints and veins [255], brain waves [256], and combinations of hand swipes, voice, and faces [257]. The authors in [149] presented a driver identification system by recognizing the unique radio biometric information [258] embedded in the CSI of commercial WiFi. A long-term driver radio biometric database was built to train a generalized DNN that is robust to the environment changes, and experiments demonstrate up to 99.13% accuracy.

B. DRIVER VITAL SIGN MONITORING

In-vehicle health/vital sign monitoring has also become attractive recently, because vital sign signals such as heart rates can help to improve other in-vehicle sensing functions such as emotion sensing [148]. Also, continuous health monitoring can reduce the risk of accidents in unpredictable and imperceivable health deterioration (such as a sudden pathological attack or heart stroke, which is difficult to be detected based on emotion or behavior sensing) of a driver when he/she is driving.

Existing works on driver vital sign monitoring include the sensor-based methods [153]–[158], vision-based methods [259]–[262] and radio frequency (RF)-based methods [263]–[275]. The sensor-based methods require wearable sensors such as photoplethysmography (PPG) [156], ECG [154], [155], EEG [153], [276], voltage-controlled oscillators [157], and electromagnetic coupled sensor [158] to capture physiological signals for vital sign analysis. They are accurate due to the direct contact with a human body but tend to be cumbersome, uncomfortable, and distracting for a driver when driving, thus hindering practical applications. Vision-based methods [259]–[262] which usually leverage a camera mounted inside a car to capture images/videos for vital sign analysis, are less intrusive by reducing physical contact than sensor-based methods, but raise privacy concerns and are susceptible to illumination conditions, which again inhabits the wide deployment. More recently, RF based vital sign sensing systems have been gaining more interests since they do not require any wearable sensor while preserving user privacy and robustness over different illumination conditions. Intuitively, RF signals reflected off human subjects will be modulated [277]–[282] by body movements including chest and heart movement due to respiration and heartbeat. As a result, one can decipher the vital sign information embedded in the received RF signals without any intrusion to a driver.

Currently, WiFi- [159], [160] and mmWave-based [283], [284] systems are the two mostly adopted RF-based approaches for in-vehicle vital sign monitoring. For example, Wang *et al.* [160] presented a WiFi-based multi-person (up to 4, a typical number of total passengers in a car) respiration rate estimation system with subcarrier selection and trace concatenation, which yields up to 98.9% detection accuracy with the respiration rate estimation error less than 1 respiration-per-minute (RPM). Moreover, it [160] also explored the feasibility of people recognition using the distribution of the respiration estimations for a certain period. Although WiFi-based vital sign sensing methods [160], [280], [281] have shown great advantages in coverage, low-cost, and excellent portability by reusing the existing on-car WiFi, they lack good spatial resolution for reliable heart rate sensing. As an alternative, mmWave [163], [264]–[268], [270]–[275] has shown superior spatial resolution because it operates in a much higher frequency, with larger bandwidth and higher integration capability to equip more antennas on a single chip, and many mmWave-based vital sign monitoring systems have been proposed. For example, the works [163], [264]–[266] (although not for in-vehicle sensing) have demonstrated the feasibility of using mmWave to extract breathing and heart rates simultaneously [163], [265] and further estimation of heartbeat variability is presented in [267], [268], [283].

Note that the aforementioned mmWave-based vital sign sensing may not be directly applied to a driver's vital sign monitoring when he/she is driving because the vital signs are very weak and thus easy to be overwhelmed by motions involved in driving. Recently, by exploring the 2D-correlation of the range-angle heat map of the received RF signal, Wang *et. al.* [271] proposed a motion compensation method to mitigate the impact of interfering motions on driver vital sign monitoring when driving by aligning and then concatenating the vital signals in different time intervals dynamically. Extensive experiments show an estimation accuracy of 99.17%, 98.94% and 94.11% for respiration rate, heart rate, and inter-beat-interval estimations, respectively.

VI. DISCUSSION

Despite the significant achievements for in-vehicle sensing applications, a number of issues still remain open for future studies. In this section, we share several possible research opportunities for interested readers.

A. EVALUATION OF THE SYSTEM

According to the surveyed approaches, there are two common limitations in evaluation. First, most of the published works are evaluated on the data collected either under simulated driving environments or practical experiments along with simple routines. Although many efforts have been made to make the simulated experiments as natural as possible, knowing a mistake does not really hurt, human beings under simulated driving experiments will have much different physiological responses from that of real-world driving [147], [285]. As a result, it is questionable whether the existing research can be generalized to practical driving. Second, different methods are usually evaluated on different datasets, and it is difficult to judge which one is better by just comparing the related approaches side-by-side because even a small difference in data may affect the performance especially for data-driven approaches. Therefore, it is worthwhile to develop highly-efficient in-vehicle sensing data collection platform and build more standard public datasets for comparison across different methods.

B. FUSION OF DIFFERENT FEATURES

Many of the existing studies [129], [131], [134], [135] have shown that joint sensing over different features together can improve performance. However, few of them have studied how much extra cost it takes during the fusion process. For example, to train a network that can leverage sensing features from both big motions (e.g., head/leg/arm) and small motions (e.g., eye open/close) may take twice or even higher computation and memory than that of utilizing just one of the features. This is because that the network may suffer from the *Curse of Dimensionality* [286] with the increment of the number of features. Hence, the efforts needed to construct the dataset and then train the network may grow exponentially. Therefore, optimization of feature fusion is important for in-vehicle sensing.

C. PERSONALIZED IN-VEHICLE SENSING

Most of the current in-vehicle sensing studies aim at improving the safety. However, with the development of automotive techniques, drivers may expect to be able to adjust the sensing functionality freely. For example, an elderly driver may want the sensing system to pay more attention to his/her own health status during driving, while another driver who has a young baby on board cares more about his/her baby on the back seat. Thus, personalized in-vehicle sensing which can meet the various requirements on different functions may be of interests.

VII. CONCLUSION

This paper presents a survey on the state-of-the-art in-vehicle sensing technology. We classify the existing research works into five topics, i.e., occupancy detection, fatigue/drowsiness detection, distraction detection, driver authentication, and vital sign monitoring. We discuss the motivation and main techniques adopted in each topic, explain how these techniques are leveraged, and analyze the limitations and possible future solutions. A high-level discussion about the evaluation and feature fusion is provided to narrow the gap between theoretical research and practical applications. Personalizing in-vehicle sensing is also covered which may inspire more research to improve driving safety while making driving experience more customized.

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