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Review and Perspectives on Driver Digital Twin and Its Enabling Technologies for Intelligent Vehicles

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***Abstract*—Digital Twin (DT) is an emerging technology and has been introduced into intelligent driving and transportation systems to digitize and synergize connected automated vehicles. However, existing studies focus on the design of the automated vehicle, whereas the digitization of the human driver, who plays an important role in driving, is largely ignored. Furthermore, previous driver-related tasks are limited to specific scenarios and have limited applicability. Thus, a novel concept of a driver digital twin (DDT) is proposed in this study to bridge the gap between existing automated driving systems and fully digitized ones and aid in the development of a complete driving human cyber-physical system (H-CPS). This concept is essential for constructing a harmonious human-centric intelligent driving system that considers the proactivity and sensitivity of the human driver. The primary characteristics of the DDT include multimodal state fusion, personalized modeling, and time variance. Compared with the original DT, the proposed DDT emphasizes on internal personality and capability with respect to the external physiological-level state. This study systematically illustrates the DDT and outlines its key enabling aspects. The related technologies are comprehensively reviewed and discussed with a view to improving them by leveraging the DDT. In addition, the potential applications and unsettled challenges are considered. This study aims to provide fundamental theoretical support to researchers in determining the future scope of the DDT system.**

***Index Terms*—Driver digital twin, human-centric deisgn, intelligent vehicles, human-machine interactions, cyber-physical systems.**

I. Introduction

Digital Twin (DT), proposed by Grieves in 2003 [1] and constantly improved since by several researchers [2–4], featured among Gartner's top ten most promising technological trends for 2018 [5]. Moreover, it is considerably popular as a multiphysics, multiscale, ultrafidelity simulation that reflects the state of a corresponding twin in real-time based on historical data, real-time sensor data, and physical models, which provides remarkable opportunities for many industrial applications [4, 6–10]. The important milestones in the development of DT are shown in Fig. 1. Recently, vehicle-to-cloud communication technology facilitated the integration of DT into the intelligent vehicle for monitoring, simulating, and maintaining the vehicle for its lifetime, which has been explored by several studies [11–16]. Combined with the smart city technique, certain researchers have also attempted to introduce the DT technology to the intelligent transportation system, thereby improving vehicle design, critical infrastructure maintenance, autonomous driving testing, and traffic optimization [17–19].

The concept of DT can be considered as an application and extension of the parallel intelligence (PI) technology [20, 21] that can be traced back to the Mirror World [22] and Shadow System [23] from the end of the 20th century. PI is devoted to exploring the collaboration and interaction between the actual and the artificial world by leveraging advanced intelligent technologies. Another typical and popular concept related to PI is the cyber-physical system (CPS) [24–26], in which physical and virtual components are deeply intertwined on various spatial and temporal levels. The CPS, which was incubated at the turn of the century, was identified as a key research area by the US National Science Foundation (NSF) in 2008 [27]. Furthermore, it is considered as one of the critical enabling technologies of Industry 4.0 [28, 29] and has been widely adopted in several sectors of society. Owing to the unprecedented growth and influence of CPSs on human behavior, Wang [30] theorized that human and social dimensions must be included in CPSs and proposed a cyber-physical-social system (CPSS) in 2010. The CPSS concept has been utilized in several fields [31], in combination with the Artificial Societies-Computational Experiments-Parallel Execution (ACP) theory for the parallel driving (PD) framework [32–35]. This approach underscores the importance of human drivers who are active in both mental and physical worlds. Building on this perspective, the CPSS-based approach emphasizes the integration of human drivers, vehicles, and information. The fundamental principle of parallel driving is to leverage the built artificial space that includes artificial drivers and artificial vehicles, to handle the complex process automated driving while keeping the design of the real vehicles as simple as possible. However, because CPSs have to synchronize with humans, the interaction between them was investigated and highlighted by the Human Cyber-Physical System Interaction (H-CPS-I) workshop of the International Federation of Automatic Control (IFAC) in 2014 [36]. Following this, the first formal international conference of the cyber-physical and human-systems (CPHS) was organized by the IFAC in 2016 [37]. In 2019, Zhou et al. [38] reported that an intelligent manufacturing system must always be considered a human cyber-physical system (H-CPS) from the perspective

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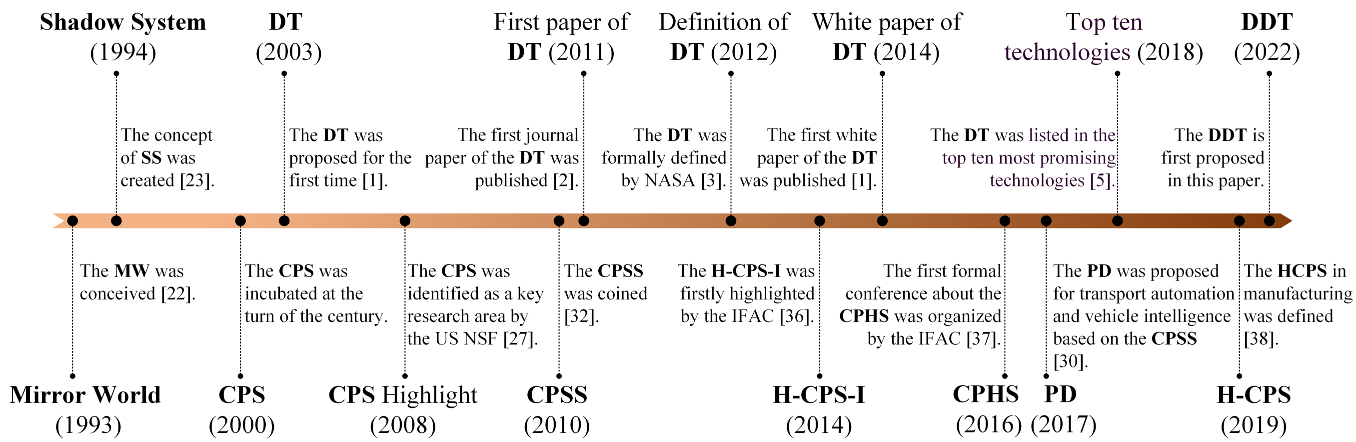

Fig. 1. History of the DT and the generalized parallel intelligence technologies.

of system constitution, i.e., it is a composite intelligent system comprising humans, cyber systems, and physical systems for achieving specific goals at an optimized level [39].

The development of the above-mentioned PI technologies, as shown in Fig. 1, show a unanimous emphasis on human involvement. A complete intelligent driving H-CPS includes three aspects: humans, vehicles, and the environmental context, as shown in Fig. 2. The current technology can better digitize and simulate the last two objects from multiple physical perspectives [40–45]; however, the digitization of humans, especially the human driver, remains challenging in view of their complexity. Existing autonomous technology requires human involvement, i.e., the driver will probably be irreplaceable for the foreseeable future. In addition, the futuristic fully autonomous vehicle must carry private passengers. Thus, their diverse personalities and preferences need to be considered to improve their acceptance and trust. The lack of a reasonable unified driver model will significantly affect the construction of the completed intelligent driving H-CPS, thereby reducing the reliability and predictability of the system. Thus, this study proposes the concept of a driver digital twin (DDT) to address the issue of driver digitization. Technologies such as advanced sensing, embedded computing, and intelligent algorithms are significant developments. They have contributed to the development of a complete DDT system that enables human-vehicle collaboration and enhances the intelligence of the automated vehicle, thereby making it more reliable. A comfortable driving environment that enables a driver to accurately feel the vehicle's response and smoothly operate the vehicle is essential. The proposed DDT system recommends a reasonable solution to tackle the above challenges; the automated vehicle is given the ability to adapt to the driver instead of forcing the driver to adapt to it. Thus, a harmonious human-centric intelligent driving system can be obtained.

With the development of digital human technology, human DT has recently been studied in the context of the health industry to reform clinical processes and hospital management. The studies primarily focused on enhancing medical care with digital tracking and advancing the modeling of the human body [46, 47]. The human DT can help researchers in studying diseases, new drugs, and medical devices. In the future, it is expected to help physicians optimize the performance of patient-specific treatment plans [48]. The bones and muscle model of the digital human can be utilized to prevent injury [49]. All collected health data (physiological data, genome, fitness sensors, etc.) help build a better digital human to respond to current and future medical problems in a faster and cheaper manner. However, these studies are limited to the physical level and treat the human body as a sophisticated machine. Although this approach is extremely challenging and complex, it is not sufficiently complex to faithfully model human behavior, humans are more complex than machines owing to their mental faculties. Thus, human driver digitization must be capable of modeling habits, personality traits, and decision patterns, which are crucial features defining a human driver. Leveraging the DDT, physiological state monitoring can help prevent potential accidents resulting from distraction or sudden illness, as well as enhance driving safety; individuality modeling can help build a human-centric driving system to improve the acceptance, trust, and user experience for intelligent vehicles. In addition, the collected real driver models based on historical data can be utilized to support the construction

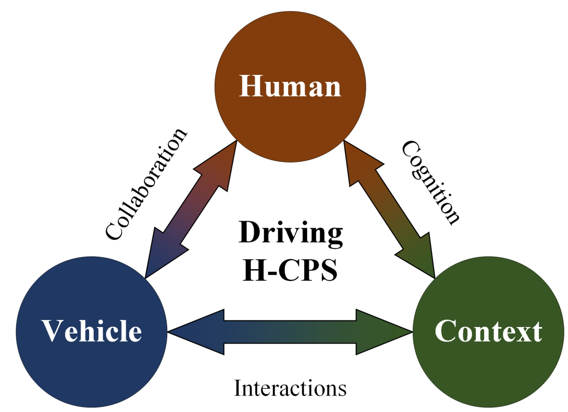

Fig. 2. A complete driving H-CPS system should include three aspects: human, vehicle, and environmental context.

of the multiagent system for the driving simulation. This, in turn, can increase its reliability and predictive ability and promote the development of the autonomous system. Recently, Wang et al. [50] proposed the HDT model for human-centric manufacturing, emphasizing the importance of the human in HCPS. It aims to accurately track and reflect human motion, perception, and manipulation activities, as well as capabilities, in order to construct a human digital representation and regulate human-machine alignment based on human proactivity. In comparison, the DDT focuses on the human driver for constructing the harmonious human-centric intelligent driving systems.

Given the growth of intelligent technologies in the past decades, researchers have studied the driver monitoring system (DMS) [51–55] from various perspectives, and related applications for advanced driver assistance systems (ADASs) have been proposed [56–59]. However, these studies primarily focused on a specific application or situation without a comprehensive perspective. Furthermore, previous studies focused on developing the autonomy and authority of the vehicle, thereby inadvertently degrading the driver's role and importance. In the future, next-generation autonomous vehicles should be more intelligent, safe, and personalized [60–69]. Therefore, the relationship between the driver and vehicle should be discussed further to support the research and development (R&D) of the futuristic automated vehicle. The proposed DDT can be considered a reasonable solution that provides a systematic theoretical framework for integrating the related modules. The built DDT system continuously tracks and improves the driving system based on the driver's style, preference, and capability by collecting the driver's data and pattern in a timely manner. Furthermore, the driving process is morphed into a data generation process. The DDT can include a wide spectrum of information ranging from the high-level comprehension of driving style to fine-grained details about the driver's behavior and attention. The generated multilevel information can be processed into big data by utilizing the intelligent algorithm, which can then be distilled into intelligence, rules, and knowledge for specific tasks and services, thereby realizing intelligent control and management as well as improving driving safety, comfort, and personalization.

The purpose and contribution of this study are to elucidate the connotation of the proposed DDT and propose its architecture and implementation approach. The enabling technologies are comprehensively surveyed and discussed, in addition to the related applications. Meanwhile, the emergence and development of DDT technology not only provides clear new ideas, methods, and approaches to realize harmonious human-centric driving but also envisage a new concept for the development of a futuristic autonomous vehicle. This study expects to establish a theoretical foundation for integrating individual research conducted on this topic and present a comprehensive review from an academically neutral standpoint.

The rest of this paper is organized as follows: Section II illustrates the concept of the proposed DDT. Section III reviews the current state of development of the enabling technologies for the DDT. The related applications are discussed in Section IV. Section V presents certain unsettled issues and potential directions for future work. Finally, Section VI summarizes the contributions of this work.

II. High-level Driver Digital Twin Architecture

DDT is being proposed for the first time through this study. It can be utilized to support human-centric intelligent driving systems and futuristic autonomous vehicles. We believe that a complete DDT system should comprise four components: the real driver, digital driver, multimodal interface, and related applications, as shown in Fig. 3.

A. Human Driver in Real World

The real driver is the physical entity and the basis, who is a data generator and an application service receptor; the real driver includes drivers of various types of commercial, engineering, and special equipment vehicles. The DDT can be implemented to address the challenges of a growing shortage of skilled drivers in specific sectors and assist aging drivers in improving the safety, smoothness, and efficiency of operation. Meanwhile, humans will always play an important role and coexist with vehicles whether the vehicle is partially or fully autonomous [70–72]. Thus, futuristic vehicles should meet human needs and recognize individual preferences to form a human-centric intelligent driving system that provides a safe, efficient, and personalized user experience.

B. Digital-Twin Driver in Parallel Space

The digital driver is the core component of the DDT system. As a virtual replica of the human driver, it should reflect the behavior of the real driver realistically, comprehensively, and synchronously. However, a fine-grained 3D model of the human driver is not required, because the human is not a machine and is more sophisticated and involved with the mind [73]. Modeling the driver appropriately is crucial for building a DDT system, and it depends on the types of applications and services that must be provided. Given the complexity of a human, the digital driver can be modeled from a comprehensive perspective that combines various aspects using advanced sensing techniques and intelligent algorithms. Furthermore, the relationships between the various aspects should be thoroughly investigated considering that they may be mutually interdependent.

Driving safety and efficiency depends on the driving pattern of the individual, and an advanced intelligent driving system should be able to understand not only the human appearance behavior and physiological state, but also the human inner intention and preference [13, 74]. Thus, the goal of the digital driver should be to replicate not only the external aspects of a human driver such as biological information, physiological condition, and attention state, but also the internal characteristics such as personality, sensibilities, and capabilities. Furthermore, modeling a real person's individuality will enable us to elicit more user-friendly and human-like interactions based on the diversity that originates from the characteristics of individuals. In contrast to the common entities with no individuality, such personalized entities can prevent misuse

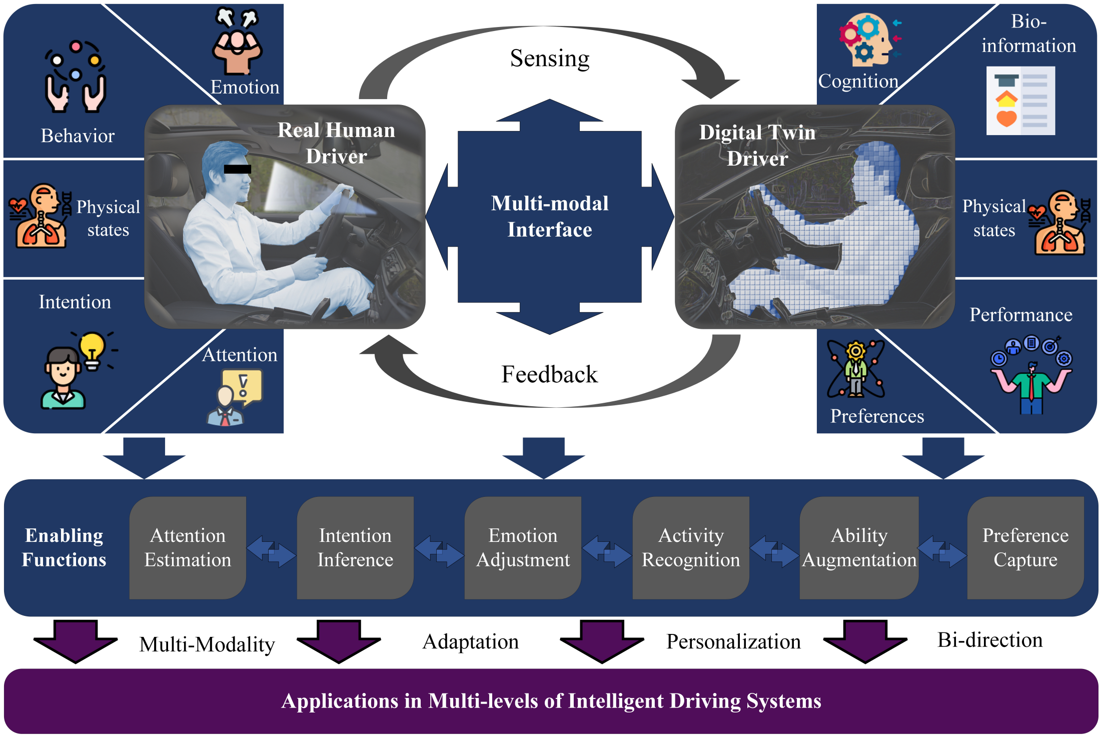

Fig. 3. Overview of the proposed DDT, including the real driver, digital driver, multimodal interface, and applications in multilevel intelligent driving systems.

of the automated vehicle and support the development of the human-centric driving system. In addition, the digital driver model should synchronize with the human driver's state in real-time to gauge mood swings and capability degradation. This personalized synchronicity with the human driver is the primary distinction between the proposed DDT and the original DT used in manufacturing.

In comparison to the current DMS system, a well-established digital driver can provide more comprehensive state information including external behavior state and internal personality pattern. Moreover, the aggregated multimodal information can improve the capability of the fine-grained analysis and recognition for the driver's state. The digital driver emphasizes entire-life-cycle monitoring, which enables the system to evaluate and predict the anomalies and the degradation of the driver's capability based on historical data; consequently, the system can provide optimal intervention to assist the driver in time. In addition, simulation is an important technique for developing autonomous driving systems [75]. The current technique can simulate the vehicle, sensors, and environment; however, real human reactions and activity in a variety of situations are difficult to simulate, which results in significant disparity between the simulation and reality. The digital driver enables a multiagent simulation supported by real models and bridges this research gap by modeling the activity patterns and personalities of various real human drivers.

C. Multi-modal Driver-Digital Twin Interface

The multimodal interface is an enabled approach and cornerstone for building the digital driver and connecting the real and digital spaces, which involves the driver's information and the driving data. Moreover, the automated vehicle is a natural platform for deploying a variety of sensors and actuators to acquire ubiquitous data. Thus, the DDT system can provide a comprehensive perception of the state of the human driver and automated vehicle and meet the requirement of the realistic feedback of the real-time and historical state of the physical entity in the related applications by leveraging the built multimodal interface.

In the past, researchers have explored various types of sensors in various applications including vision-based (RGB, depth, IR, Lidar, etc.), physiological-based (EMG, EEG, ECG, etc.), and driving-based sensors (steering, pedal, speed, IMU, etc.) [51, 76]. The collected data from these sensors can reflect the various behavioral patterns, conditions, and preferences of the driver from several perspectives. The DDT system must integrate these sensors and actuators to create a multimodal interface that can provide comprehensive sensing and feedback. To this end, the sensors should complement one another to support the development of a complete digital driver; all elements must communicate, interact, integrate, and merge. Meanwhile, it entails data acquisition, definition, transmission, calibration, source protection, fusion, and mining among other processes to handle large amounts of real-time, multidimensional data. Furthermore, multimodal fusion is potentially a key technology, which can be implemented at different levels, including feature-level, model-level, and decision-level [77]. The feature-level fusion requires prior knowledge to integrate the multimodal features that might enhance the interpretability of the model. However, it requires significant data calibration and synchronization. Model-level fusion includes different structure models that are utilized to handle and extract the multimodal representations. Fortunately, the advancement of neural networks (NN) provides various types of models that can tackle varying kinds of input data, and can be easily integrated. These types of NNs such as many multi-branch or multi-streams networks are proposed to handle the multimodal input [78, 79]. The NN-based methods enable the model to learn the fusion pattern in a data-driven way, leading to a robust and accurate fusion performance. Decision-level fusion means that the result vector of each modality feature is respectively obtained by their suitable model. Thus, the rule-based approach can be utilized to allocate the different weights for each modality result. However, this approach is sensitive to outliers and cannot tackle complex and high-dimension vectors. To improve the decision performance, the machine learning(ML) classifier and regressor can be adopted to learn the internal pattern. In addition, ensemble machine learning can also be leveraged to increase decision efficiency.

Sensors should achieve precise recognition for driver activities to improve the quality of the digital driver; further, ultralow latency and ultrareliable communication technology should be investigated [80–85]. The interaction design is also critical because it must address the issue of seamless interaction and state feedback to support the dynamic collaboration and resource sharing between the physical world and digital world. The interface must consider human acceptance, such as the human's resistance to some intrusive sensors, which requires the unobtrusive and miniaturization of the sensors. Thus, the researcher must thoroughly and carefully investigate the appropriate and available configuration of the multimodal sensors and interaction interface.

D. Key Applications of the DDT

The applications are the ultimate goal of the DDT system. They must be capable of leveraging the various enabling functions to assist the driver intelligently and securely. Furthermore, as the applications are a vital link between the virtual and real worlds, enabling the DDT system to operate in a closed-loop mode. Several related applications such as ADAS, shared control, and driver safety monitoring have already been studied for decades. Implementing the DDT system can further improve the user experiences of these applications and lead to new possibilities.

The applications can be classified into three paradigms: *physical-to-digital*, *digital-to-digital*, and *digital-to-physical*, which are applicable to different levels of autonomous driving systems. The physical-to-digital paradigm focuses on leveraging human intelligence to optimize the intelligent driving system by learning the real driver's behavioral pattern. The DDT system provides a possible implementation solution by digitizing the driver's behavior and decision-making pattern in a variety of situations. The digital-to-digital paradigm focuses on the ability to develop group intelligence and leverage expert models to improve the individual ones, which overcomes the physical limitations. Moreover, the mutual interactions between the various functions lead to an improvement in each function. Finally, the digital-to-physical paradigm focuses on using the assistance of the digital system to improve the real driver's control and state. If a life-long DDT system is constructed, the real driver's capability can be enhanced by a past driving model of themselves in the event of degraded driving capability.

Based on the DDT system, the applications can exploit the real-time and historical data of drivers and vehicles, thereby shifting the system's operation from the prior knowledge-driven approach to a data-driven one. Moreover, the development of related applications can be changed from passively demand-driven to positively DDT-mined innovation. Thus, data-driven DDT can reinforce the related applications that adapt to the driver's preferences, styles, skills, and patterns, which makes the driver-vehicle coexistence and collaboration safer, more efficient, and user friendly. Furthermore, more virtual-reality-fusion applications can be explored to improve interactivity by leveraging the built-in digital drivers.

III. Key Functions of Driver Digital Twin Technology

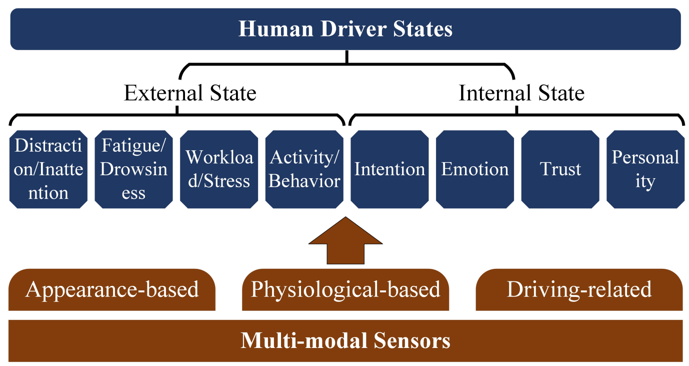

Fig. 4. Taxonomy of the existing studies for the human driver monitoring system.

To build a complete digital human driver, a variety of driver states should be obtained, modeled, and incorporated. The current research for driver modeling revolves around the DMS that has been widely used in intelligent vehicles [86]. Researchers have investigated it from various perspectives to monitor various driver states as shown in Fig. 4. These monitored conditions can be classified into external and internal conditions. The external state primarily comprises the state that exists consequent to external behavior such as distraction activity and drowsiness. The internal state is related to the inner consciousness and personality of the driver, including components such as intentions, emotions, and trust. The states are monitored by the multimodal intrusive and nonintrusive sensors that can be summarized into three categories: appearance-based, physiological-based, and driving-based. Appearance-based sensors include the RGB camera, depth sensor, infrared sensor, etc. They are utilized to obtain facial and bodily movements. The physiological-based sensors monitor the various physiological factors, including the heart rate, brain waves, and blood pressure. The driving-based sensors collect vehicle-related data during the operating process, such as the steering data, braking information, speed, etc.

Existing studies focus on a specific task and ignore the collaboration between various functions, thereby limiting recognition performance. Therefore, a unified digital model of the driver involving external and internal conditions is indispensable to endow the system with robust, precise, and time-variant sensing capabilities to assist the human driver. The data structure shown in Fig. 4 can also be utilized to model the DDT but from a unified perspective.

A. Driver Distraction Detection

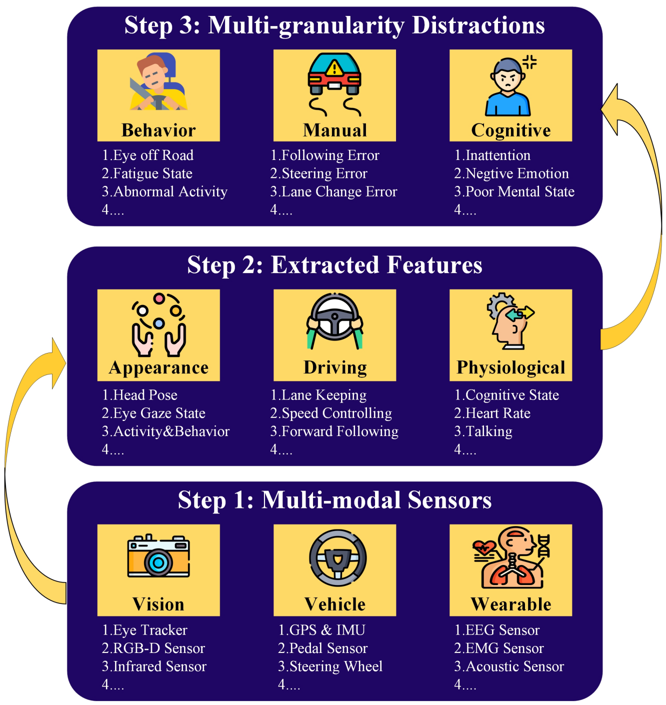

Fig. 5. General framework of driver distraction detection.

Driver distraction is a primary cause of road accidents and has attracted considerable research attention [76, 87]; it has consequently become one of the typical tasks of the DMS. A variety of nonintrusive and intrusive sensors are utilized to detect the driver's distractions at different levels of granularity by leveraging ML algorithms [88, 89]. The nonintrusive sensors, including the vision-based and vehicle-related sensors, can be used to tackle high-level behavior-related distractions such as abnormal activity [90–93], distracted pose [94–97], false operation [98, 99], and inappropriate focus area[100–103]. In contrast, intrusive sensors can precisely assist in evaluating the driver's inner consciousness and cognitive state [53, 104–106]. However, some intrusive sensors can be cause significant discomfort and affect the driver's movements and pose. Consequently, the obtained distraction detection results are biased and affect the final interpretation. Furthermore, this limits the potential application of some of these sensors to research-related endeavors.

Currently, the definition of distraction is ambiguous, and previous studies have approached it with varying degrees of granularity. One typical approach is recognizing distractions based on the driver's activity. [107] designed a typical driver activities recognition system based on a vision-based sensor leveraging deep convolutional neural networks (CNN). The sensor could identify seven common driving activities by detecting the driver's body posture; similar work can also be found in [108–111]. This approach typically achieves almost 99% accuracy in detecting the limited driver activity. It performs the classification task by leveraging the powerful representation capability of the deep learning (DL) based models. However, this method has several limitations. Firstly, actual human activities are diverse, which may adversely affect the performance and robustness of the trained models. Thus, technology capable of grasping context, such as the video-text approach [112], can be utilized to tackle this challenge. Second, these CNN-based methods typically rely on large labelled datasets to improve recognition performance, which necessitates further investigation into advanced semi-supervised and self-supervised approaches, such as the contrastive learning method [113]. Moreover, the computational efficiency is an inevitable barrier for practical applications. Thus, further model compression and optimization technologies are required [114, 115]. In addition to the activity of the body, the driver's head and gaze is also indicative of distractions; accordingly, several studies focused on detecting the driver's gaze on the corrected area or road [100–103]. These methods adopt a similar approach to those focusing on bodily movements and tackle distraction recognition as a classification task by leveraging the various CNN-based models, which achieve more than 90% accuracy. The primary difference is that the model input is a facial image or features rather than a full-body image.

The driver's distraction is also related to the mental state in addition to the appearance-based distraction. Therefore, the electroencephalographic (EEG) signal is utilized to measure the brain activity for the early detection of driver distractions [105, 106]. Furthermore, measurements of the reaction time in addition to other physiological signals can be leveraged to evaluate the driver's concentration [116]. [117] combined the various physiological data including palm electrodermal activity, heart rate, and breathing rate with facial-related features to detect the four types of distractions, and a spectro-temporal ResNet (STRNet) was proposed to handle the multimodal features. In addition, this study also analyzed the different modality features for the final detection performance. Consequently, it demonstrated that the most informative modality depends on the type of distraction, with visual features providing the most information overall. Similar work can be found in [118], which adopted physiological (electrocardiogram (ECG), galvanic skin response), behavioral (accelerometer and gyroscope), and vehicular (CAN-Bus) signals with various ML-based recognition models.

In addition to the state of the driver, manual information can also be utilized to evaluate the level of driver distraction. [98] as well as the [99] leveraged the eye-steering correlation structure to indicate the driver's state. These studies demonstrate that the correlation is useful, but not more robust than the previously discussed features. [119] utilized the broad learning and incremental learning system (BLILS) to recognize vehicle misbehavior using the vehicle steering information,

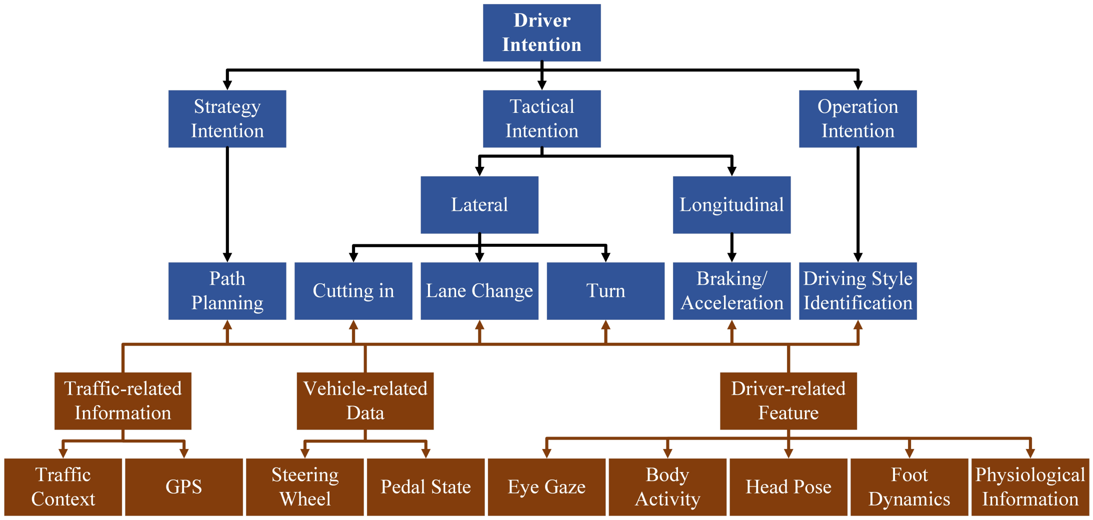

Fig. 6. Overview of the driver intention prediction.

such as vehicle speed & acceleration, direction of travel, vehicle position, transmission delay. The experimental results show that the proposed BLILS can recognize distractions faster and more accurately than the conventional ML and DL methods, while possessing excellent robustness and scalability for practical applications. [120] presented a driver workload detection approach based on the driver's physiological, and vehicle signals as well as traffic contexts such as congestion level and traffic events, and evaluated the proposed method on the real driving scenarios data. In addition, smartphones have been utilized in several studies to monitor the driver's behavior by leveraging the mounted multimodal sensor of the phone [91, 121–124]. However, the mobile-based approach, with approximately 80% accuracy, cannot compete with the methods using the driver states, unless combing of the driver face image is performed to detect distractions.

Existing studies can be summarized as shown in Fig. 5. The detection of multigranular distractions can be implemented by various types of features by leveraging the multimodal sensors. Previous studies have reported impressive performances in recognizing specific distractions with more than 95% accuracy. One study [117] demonstrated the varying importance of a variety of modalities for monitoring different types of distraction. In contrast, the literature highlights the absence of a unified solution that can handle all types of distractions for various scenarios. Furthermore, the existing methods, despite their excellent performance, largely ignored individual diversity. The proposed DDT concept can be utilized to overcome these challenges by providing a unified approach with multimodal sensors to extract various types of features. It can achieve this by leveraging the representation learning approaches and the DL-based recognition models. Moreover, studies have demonstrated that utilizing multiple sensors can improve the overall performance [98, 99, 111, 117, 118]. In the future, an approach with multiple sensors must be explored to enhance the reliability and intelligence of the distraction detection system.

B. Driver Attention Estimation

Driver attention estimation aims to determine the driver's focus area to support the conditional driving system and provide intervention or assistance in critical scenarios [125, 126]. Attention estimation is related to distraction detection; however, it goes a step further in understanding the driver's state and not only detects whether the driver is distracted but also estimates whether the driver's attention is on the right area such as the road, traffic light, and crossing pedestrians.

A typical approach is to build a mapping model between the context of the external scenario and the driver's field of attention. The visual field of the driver is divided into several sub-fields or targets. In [103], a naturalistic driver behavior dataset with six predefined attention zones was created for various driving scenarios. A random forest classifier was utilized to generate a set of probabilities for each gaze zone based on the features of the head and face, and a recognition accuracy greater than 90% was achieved. A driver focus corpus was built for a parked vehicle in [127] that divided the driver's attention into 18 zones based on RGB and depth sensors. A pre-trained VGG16 model was fine-tuned to classify the gaze zone with an 84% accuracy. In this study, an end-to-end approach was adopted using the color driver image without extracting the facial features. A similar CNN-based approach was utilized in [128], where a driver gaze in the wild (DGW) dataset was collected with 9 labeled zones. However, compared with other datasets, the DGW employs more subjects to improve the diversity of the dataset, thereby resulting in a lower accuracy of approximately 60%. AutoPose [129] collects driver attention data from an infrared camera and an RGB-D camera using a driving simulator; these data include six gaze zones, as well as head poses and driver activities. A multimodal driver monitoring dataset with 21 gaze targets and driver head poses was presented in [130]. A head-mounted inertial sensor was used in [131] to determine the ten focus spots of a driver in a vehicle cabin, in which several ML classifiers were utilized to predict the gaze attention. Furthermore, the experimental results demonstrated

TABLE I
EXISTING DATASETS FOR DRIVER ATTENTION ESTIMATION

Dataset	Scenario	Sensors	Gaze Annotation	Subjects
MIT [103] (2016)	Highway	RGB-driver	6 Gaze zones	50
DG-Unicamp[127](2019)	Parking	RGB-driver Depth-driver Infrared-driver	18 Gaze zones	45
DGW[128] (2020)	Parking	RGB-driver	9 Gaze zones	338
Autopose [129] (2020)	Simulator	RGB-driver Depth-driver Infrared-driver Mo-Cap	6 Gaze zones Head pose Driver activity	21
MDM [130] (2021)	Parking Driving	RGB-driver,back,mirror,road Depth-driver,Infrared-driver Fi-Cap,Microphone,CAN-BUS	21 Gaze zones Head pose Driving data,Audio	59
DR(eye)VE [132] (2018)	Highway Countryside Downtown	RGB-road Eye tracking(collecting)	Gaze attention map	8
BDD-A[133] (2018)	Critical driving situations	RGB-road Eye tracking(collecting)	Gaze attention map	45
DADA-2000[134] (2019)	Accidental driving scenarios	RGB-road Eye tracking(collecting)	Gaze attention map	20

the efficiency of the head-mounted inertial sensor that can achieve an accuracy greater than 96%.

Another focal point of driver attention estimation is predicting the driving gaze map of the scenario, which indicates the area that might attract the driver's attention rather than that the driver actually focuses on. A representative study of this type is the DR(eye)VE project [132] that assembled the driver's gaze map with the use of gaze tracking glasses worn by the driver while driving in various scenarios with varying conditions leveraging. Furthermore, several datasets, such as the BDDA dataset [133] that focuses on critical driving situations, and the DADA-2000 dataset [134] that focuses on accidental driving scenarios, were developed. To predict the driver's gaze map, U-Net [135] type of models were adopted to learn the attention pattern. In addition, the optical flow and semantic information were also utilized to improve predictive performance. According to the existing experimental results, predicting driver attention remains challenging because of the complexity of the scenario and the human driver's individuality.

The typical datasets for driver attention estimation are listed in Tab. I. Existing appearance-based approaches of gaze zone estimation can perform well and achieve outstanding accuracy by leveraging deep-learning-based technology. Leveraging complementary information, such as head pose, can further improve the estimation performance compared with the end-to-end model. However, these methods only consider the external appearance information of the driver. Thus, in scenarios where the focus of the gaze and mind do not coincide, estimation accuracy declines drastically. Thus, the DDT model combined with cognitive state information can help improve the robustness and accuracy of driver attention estimation.

C. Driver Intention Inference and Prediction

In addition to the external driver state information, the vehicle needs to understand the driver's intention to generate appropriate assistance and collaborative control strategies. Current studies focus on specific tasks or scenarios such as lane change intention [136–138], braking intention [139–141], and acceleration intention [142], and they can be summarized as shown in Fig. 6.

When predicting driver intention, lane change is the most commonly encountered intention. Here, the target includes the ego-vehicle [136, 143] and surrounding vehicles [144]. The prediction of surrounding vehicles utilizes trajectory information, obtained based on the GPS and Internet of Vehicles(IoV) technology, as the input to infer the intention. Such methodologies found in studies on ego-vehicle [144–149] and several deep learning-based models, particularly the recurrent neural network (RNN), are proposed for handling the traffic information of the ego-vehicle and surrounding vehicles. Vehicle maneuvering patterns are also investigated to predict and estimate the vehicle lane-changing state [150]. In addition to the driving data, the driver's states and posture are frequently utilized to improve the prediction accuracy. Head pose is a common indicator of driver intent, and measuring the head pose is less time-consuming and more reliable in unfavorable driving conditions [94]; therefore, it is often used to infer driver intent [151–153]. Furthermore, gaze can accurately reflect driver attention, and is commonly adopted to act as a classifier that predicts driving intention, as demonstrated in [138, 154–156]. In [137], a vision-based driver lane-change intention inference system was introduced; this system utilized multiple driver-related signals and the vehicle data acquisition system to handle time-series driving sequences and temporal behavioral patterns. According to the survey in [136], lane change intention can be predicted with an accuracy greater than 90% in the driving simulator. In contrast the on-road accuracy is generally 70%-90%, where the CAN bus data is essential for the on-road inference. Moreover, the driver's facial information can also be captured by leveraging the RNN-based model to achieve an accuracy greater than 90%.

Longitudinal maneuvers such as braking and acceleration can cause the automobile to lurch and can result in potential safety issues. The reliable prediction of the intention to brake or accelerate can enhance safety of driving through preventative actions. [142] proposed an intention-oriented model for longitudinal dynamics based on the commonly available signals on the CAN bus of modern vehicles. [139] presented a novel braking intention identification model based on the LSTM network to recognize three levels of braking: slight, normal, and hard, in which braking-related data obtained from the speed sensor, gyroscope, and pedal force sensor, were utilized to achieve a predictive accuracy greater than 95%. Further, the driver's cognitive signal was investigated to detect the intention to perform emergency braking [140, 141], with an experimental accuracy greater than 90%. [157] investigated the mechanism of intentional behavior and proposed a psychological perception–action (P–A) model that enables the intentions of drivers to be characterized at each level of the P–A hierarchy in terms of a variety of driver signals.

The steering intention exhibited by the driver was studied in [158] to enhance human–vehicle understanding. A novel deep learning-based time-series model was proposed to model the relationship between the neuromuscular dynamics and the steering torque by leveraging the electromyography (EMG) signals of the upper limb muscles; this model can be utilized to predict both the continuous as well as discrete steering intentions. [159] demonstrated a personalized driver intention prediction system at T intersections devoid of traffic signals by learning in-depth driving behaviors; various classifiers were evaluated to link low-level vehicle states to high-level driving behaviors. An ensemble learning-based driver steering intent recognition strategy was developed in [160], and a nonlinear model predictive control algorithm was designed and implemented to generate haptic feedback for lateral vehicle guidance, assisting the drivers in accomplishing their intended action.

Figure 6 shows that the utilized input data for driver intention includes traffic context information, driver states, and vehicle dynamic data, in addition to their various combinations to predict the various maneuvering intentions. Existing studies demonstrate that driver intention prediction is a context-aware and multimodal representational task. Thus, current models suffer several limitations. In conclusion, a unified model integrated with multiple indicators is indispensable for improving the robustness, generalizability, and accuracy of the prediction to tackle various scenarios rather than a specific situation.

D. Driver Drowsiness Detection

Driver drowsiness is another important factor that causes traffic accidents with a high fatality rate. Therefore, it has attracted considerable attention among researchers [51, 52]; however, despite its similarity to driver distraction, they are not identical. The drowsiness alert function is becoming increasingly common in intelligent vehicles [161]. From a methodology perspective, a driver's drowsiness can be detected in a manner similar to that used to detect driver distraction, as shown in Fig. 7, where three types of features are commonly used: physiological [162–164], maneuver [165–167], and behavioral [168–170].

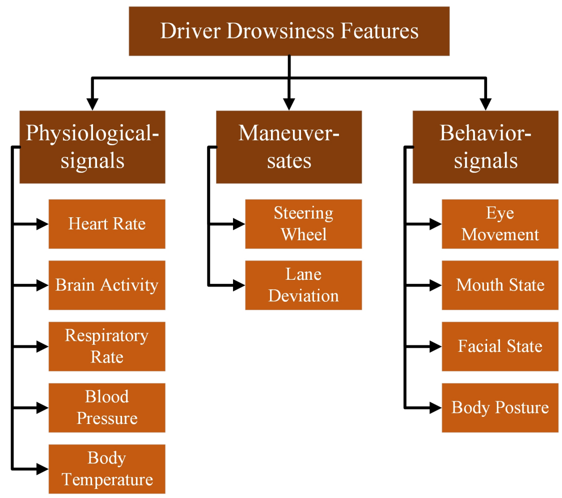

Fig. 7. Commonly used features for driver drowsiness detection.

Drowsiness is more concentrated in the facial [169, 170] and cognitive-related features [171]. For example, [162] established a technique for detecting driver fatigue by analyzing two distinct features: eye movement and bio-signals. A wireless, wearable brain–machine interface (BMI) system was proposed in [104] for signal sensing and processing the detection of driver drowsiness. In addition, the correlation of the EEG power spectrum and the driver's behavior was demonstrated in [172]; they found that the EEG pattern of the drowsiness varies with the individual. Therefore, subject-dependent and generalized cross-subject detection models for driver drowsiness were investigated. [173] combined the electrooculogram (EOG) with the EEG to monitor the driver's vigilance to improve model performance, and a novel LSTM-based model with a capsule attention mechanism was proposed to learn the multimodal representation. The respiratory signal was utilized in [174] to detect drowsiness using an inductive plethysmography belt, which analyzed the respiratory rate variability (RRV) to determine the driver's state.

Like driver distraction, current research on driver drowsiness focuses on specific types of drowsiness by leveraging specific types of features. The advancement of DL networks has also contributed to impressive predictive performance in such systems. Certain studies [173] attempted to fuse multimodal sensors in a simulator that enable systems to detect the fatigue more robustly and accurately but lack real driving evaluation. Furthermore, [172] found that system performance may decrease rapidly when the non-personalized drowsiness detection models are applied to different drivers. These studies indicate that a personalized and multimodal integrated representation in a real driving scenario is required to enhance the performance of the drowsiness monitoring system.

E. Driver Emotional State Monitoring

The emotional state of the driver is critical for driving safety, particularly in cases of road rage, which has been investigated in several studies [175–178]. These studies indicate that the driver's emotional state critically impacts driving performance, and that the negative state is associated with aggressive driving that leads to numerous traffic accidents. Emotion recognition has attracted considerable attention in the past decades [179, 180] because emotions influences human decision-making during driving [181]. Consequently, the emotional state of humans is investigated in a range of research areas of psychology and cognitive science. Two types of approaches have been adopted to analyze human emotional states: discrete [182] and continuous [183, 184]. The discrete approach categorizes emotional states into specific states such as happiness, surprise, sadness, and anger. The continuous approach uses a continuous space to indicate the emotional state. In view of its importance to automated driving systems, emotion recognition has been studied from various perspectives with a variety of sensors using machine learning technology [185].

Emotional conditions are associated with discernible physiological responses [179], which include ECG [186], EEG [187], EDA [188, 189], and BVP [190]. Several studies utilize wearable physiological sensors to detect the emotional state of the human driver. For example, [187] presented a multimodal database that comprises EEG and ECG signals recorded during affect elicitation via audio-visual stimuli, and an SVM-based method was proposed to recognize the emotions of individual participants. [191] leveraged the nonlinear complexity of heart rate variability (HRV) to assess an individual's emotional state. Similarly, [192] suggested that increased HRV can be an indicator of the ability to recognize human emotions.

The vision-based approach was investigated by several researchers owing to the fact that emotions are readable from facial expressions. For instance, [193] proposed a probability and integrated learning algorithm for high-level human emotion recognition in music videos. This algorithm adapted emotion classification fuzziness based on the mechanism of uncertainty artificial intelligence. [194] presented an integrated network approach for recognizing facial expressions using facial landmarks. [195] combined head poses and gaze with facial expressions for continuous emotion recognition; an attention mechanism was used to guide the model to extract highly relevant information. The asymmetric bilinear factorization model was used by [196] to decouple linguistic and affective information from the face. [197] proposed a facial dynamics map combined with optical flow to characterize the movements of microexpressions at various granularities.

Other studies combined the physiological information with the appearances feature to improve recognition performance. [198] proposed a DL-based framework for recognizing the driver's emotions using visual images of facial features and heart rate data over time. A novel convolution bidirectional LSTM model was developed to extract the features and classify them into five general categories. [199] used the heart rate and animation units to aid in the detection of facial expressions in videos. [200] presented a multimodal sensor fusion framework for studying both basic and complex emotions, including eye tracking, biometrics, and EEG signals. Acoustic features were also leveraged in certain studies. For instance, [201] demonstrated an acoustic features-based speech emotion recognition approach, and [202] used an SVM model to classify five emotional states for automatic speech emotion recognition.

According to existing research, emotion recognition relies on multiple features or sensors because emotions are related to the physiological condition, cognition state, and facial features. An accuracy greater than 80% can be achieved using classic ML models and over 90% with DL models [179]. However, considerable research and development is required before vehicles can recognize the full spectrum of the emotional states of drivers. Therefore, an interdisciplinary approach including psychological investigations must be considered. The fusion of multimodal data can certainly provide additional information to improve accuracy. Ubiquitous, flexible, and pervasive wearable technology should also be further investigated. Existing wearable devices equipped with physiological sensors, such as smartwatches, are a good starting point and can be integrated into the driver monitoring system. Furthermore, emotions are specific to individuals. For example, the reasons behind the driver's negative emotions typically depend on traffic conditions to which the driver is subjected over a certain period. In addition to external influences, certain internal personal factors can also frustrate the driver, such as the personality reaction to stimulation and the cognitive state, which includes pressure, stress, and anxiety. Different drivers exhibit various cognitive and emotional patterns. Thus, DDT with comprehensive modeling can achieve robust recognition by focusing on modeling the individual emotional pattern.

F. Monitoring of Driver Trust on Vehicle Automation

In addition to the aforementioned factors, the driver's attitude toward the assistance provided by the automated vehicle (AV) in uncertain scenarios can be reflected in their level of trust [203]. Accidents can occur when drivers mistrust the AVs, especially in complicated and unanticipated scenarios. In such scenarios, ensuring that the driver completely understands the automated decisions can be impractical [204]. Thus, building an appropriate level of trust becomes a crucial issue for safe operation, which has attracted considerable attention [205–207].

Human trust is a sophisticated implicit variable that involves several factors such as the psychological, sociological, and neurological status [208]. According to existing studies, human trust relies on the driving performance of the AVs [209–211]. Moreover, high levels of initial trust generally stem from an excellent illustration of the system capability [212, 213]. In addition to increasing the capability, comfort, predictability, and transparency of the AV to gain human trust, we can also investigate human factors to avoid inducing overtrust or distrust. This is typically time-variant, and it can be influenced by the stress, workload, cognition, scenario, and personality of the driver [214, 215]; even the educational background and usage experiences can be associated with trust [216, 217]. Li et al. [218], for example, investigated the relationship between driver personality and driver trust in the AV and discovered a significant correlation between Openness and driver trust. Xing et al. [74] summarized all influential factors into three categories: prior, short-term, and long-term factors. Prior factors include the personal traits and background that can affect the human's acceptance of the AV prior to usage. Short-term factors include driver-related states and driving performance, whereas long-term factors include user experience and familiarity after a certain period. Several studies have proposed different approaches to measure the level of trust and optimize the AV to determine the driver's trust status. The different approaches include questionnaires, workload & anxiety estimations, detection of trusting behaviors, and preference studies [219–223]. Other studies have attempted to evaluate trust using external driver behavior features and response time, and their results indicate that the level of trust varies with the reaction times of control recovery [224, 225].

Trust is a crucial factor that should be considered in the design of the AVs; otherwise, it will tend to treat the driver as a by-product of the AV and easily cause automation misuse. Dynamic trust monitoring is indispensable for providing timely intervention to ensure that the human driver trusts the system to an appropriate level. Furthermore, trust evaluation remains a challenging problem because it involves multidisciplinary knowledge and information. DDT provides a reasonable solution to this problem based on comprehensive modeling and time-variable characteristics.

G. Personalized Driver Behaviour Recognition

Drivers can have various types of driving behaviors, and they prefer automated vehicles with a driving style that is similar to theirs [226]. Ensuring such parallelism can enhance the acceptance and comfort the human driver experiences. However, a human is more flexible when tackling different scenarios. Therefore, a personalized driving system is necessary and important, and it can be built by observing and learning the driver's behavior and decision-making patterns.

The acceptance of different driving styles by different drivers and their influence on the drivers have been discussed in [227] and [228]; the designed experiments demonstrated that younger drivers exhibited a greater preference for their own style compared with older drivers. Furthermore, it was demonstrated that different drivers have diverse requirements and preferences. A similar study was conducted by [229]. They investigated the preferences of the human drivers including assertive and defensive styles, under three autonomous vehicle driving styles (defensive, assertive, and light rail transit). The results showed that the defensive driving style was preferred and that variations exist between participants related to their own driving style. Furthermore, the study indicated that future autonomous vehicles should indicate and adjust the driving style to the preferences of the human driver to maximize comfort in the travelling experience. [230] also found that drivers prefer a driving style significantly more defensive than their own, and that they tend to think it is their own. Furthermore, the preference was found to depend on specific scenarios.

Based on the above assumptions, [231] proposed a human demonstration learning approach to teach the vehicle to learn the desired driving style instead of using manual settings. This approach modeled the driving style of each individual by leveraging the inverse reinforcement learning approach to obtain suitable driving parameters. [232] presented a human-like decision-making system for autonomous vehicles that formulated different driving styles and social interaction characteristics based on game theory to enhance driving safety, ride comfort, and travel efficiency. [233] proposed a new predictive control method based on the models of human behaviors and vehicle dynamics to improve the performance of the longitudinal brain-control driving; this method was developed with the intention of maintaining vehicle rear-end safety and driver ride comfort while ensuring drivers have maximum control authority.

Furthermore, personality is a diverse and sophisticated characteristic and involves various indicators that are difficult to obtain unless it is observed from a comprehensive perspective. The driving data and reaction information for a variety of situations can be collected to reflect the driver's personality by leveraging the DDT system. Personality modeling is one of the most critical enabling functions of the DDT that can lead to the development of a personalized intelligent driving system.

The above subsections reviewed studies focused on driver modeling; these studies investigated the different functions from various perspectives. Certain studies showed that the combination of multiple sensors can improve system performance. For example, [121] utilized a smartphone's multimodal sensors to identify the states of the driver that signaled danger, including drowsiness, distraction, aggressive driving, and high pulse rate. Furthermore, they proposed a cloud system architecture to collect statistics from vehicle drivers, analyze them, and finally personalize the driver's smartphone application. [234] proposed a novel danger-level analysis framework for dealing with high variety and high volume problems of multisource driving data including driver-, vehicle-, and road-related information. Therefore, the integration of multimodal sensors into the DDT can further enhance the capability of driver modeling. Furthermore, the existing methods rely on the data-driven approach, and the utilized data are collected from various human drivers. However, humans are diverse, and it is impractical to utilize the same criteria to evaluate the state of different people. This is demonstrated in [235], which established a framework for analyzing the driving behavior of professional drivers and evaluating the impact of novel safe driving concepts on different driver profiles. The results revealed that drivers with varying levels of experience exhibited varying levels of performance when applying safe and anticipative driving behaviors. Consequently, the DDT system can be utilized to build a personalized model to achieve precise detection. Furthermore, the different states of the driver are interdependent and can be supplemented with others to improve the performance of the recognition model,

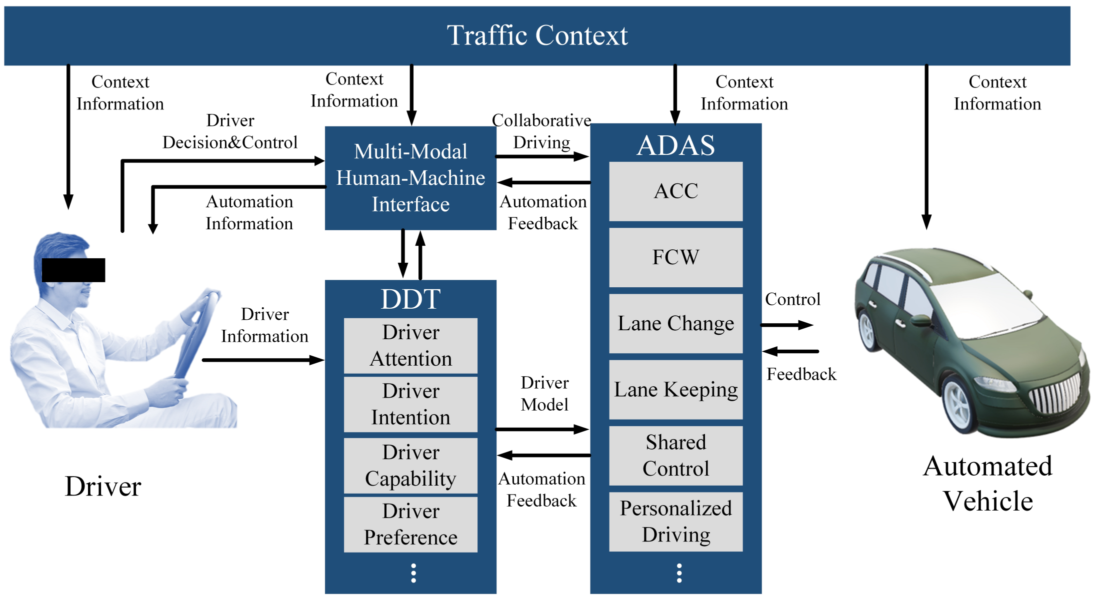

Fig. 8. A general framework of the ADAS leveraging the DDT system.

as demonstrated in [236]. They developed a driver intention recognition model that involves the driver's emotions; various resources including visual features, auditory information, and olfactory data were used to induce the driver's emotions.

The literature survey reveals that existing studies tend to fall into a kind of stagnation. Although several models have been developed to tackle a specific task for certain scenarios, hardly any have performed ideally in practice owing to the complexity of the actual scenarios and human driver. In contrast, the DDT system could provide a comprehensive, personalized, and time-variant representation of the driver's state that enables the AV to thoroughly understand the driver's state and improve its performance. In addition, existing studies focus on recognizing the explicit activities or states of the driver to achieve a specific function; however, implicit driving patterns and styles also need to be investigated further to ensure support for downstream applications. This remains challenging owing to the non-deterministic nature of the implicit patterns and the high degree of inter- and intra-driver variability. Therefore, the DDT is expected to provide a novel avenue of research for future studies, and consequently lead to significant development in this field.

IV. Representative Applications of DDT in Intelligent Vehicles

This section aims to summarize the DDT-enabled key applications and discusses how the DDT can be utilized to further improve the intelligence, personality, and adaptivity of driving automation systems at multiple levels.

A. DDT in Advanced Driver Assistance System

The partially autonomous vehicle is expected to play a dominant role in the future based on the current pace of development of automated driving technology. ADAS would be a standard configuration for intelligent vehicles, and it can be enhanced with more assistance functions and utilized in a broader range of applications. The ADAS system can mimic or predict the driver's behavior and intention by leveraging the driver's pattern and style information provided by the DDT, such as [237] proposed an LSTM-based model which utilizes data on the driver's gaze and head position as well as vehicle dynamics data to predict the driver maneuver. Thus, it can provide personalized and adaptive assistance to improve the driving safety or experiences, as shown in Fig. 8.

1) DDT for Adaptive Cruise Control: Adaptive cruise control (ACC) is a typical assistance function for longitudinal control of vehicles. It simultaneously maintains a constant speed set by the driver and a desired time gap to the leading vehicle. Conventional ACCs pre-define a set of time gaps from which to select. Certain studies have attempted to involve the personality factor to improve the self-adaptation of ACCs [59, 238–240]. In [241], a human-like car-following nonlinear model predictive control controller is developed based on a calibrated human-like Wiedemann model. [242] collected the driving data of multiple drivers and built several driving style profiles. Subsequently, the driver was assigned to one of these profiles for determining the ACC control strategy; this strategy included the engage and disengage ACC [242], and the stop and go strategy [243]. [244] and [245] adopted another approach. The individual driving style was observed and a personalized strategy was developed to improve user experience. In this study, different learning algorithms were proposed to acquire the individual driver's driving style [246–249]. Other studies developed two distinct modes to achieve personalization: learning and running [250]. The driver could manually activate the learning mode to observe the driving parameters, while the running mode was utilized to deploy the learned control model. Meanwhile, other researchers recognized the significance of online learning and proposed the personalized ACC system, which can adapt to driver control strategies in a dynamic traffic environment [246].

2) DDT for Forward Collision Warning: A forward collision warning (FCW) system can alert the driver to avoid an impending collision with the leading vehicle or object. [251] and [252] proposed a statistical approach to model driver behavior, which can be used to adaptively determine the warning activation threshold and reduce the false warning rate; this is similar to [253]. [254] utilized facial information and EEG signals to estimate the brake reaction time of individual drivers to optimize the timing of the warning. Moreover, different drivers behave differently in a given scenario. Thus, personalized FCW systems can reduce the false alert rate and adaptively adjust the warning time to provide drivers with a reaction time appropriate to their driving capabilities.

3) DDT for Lane-keeping and Lane Change: Lane-retention and lane change are typical functions of the ADAS system. They aim to assist the driver to stay in or change the lane by estimating their intention based on the personalized driving model. [255] proposed a learning approach to model driver behavior and improve the lane departure alarm system. [256] developed a personalized vehicle steering system that can adaptively assist the driver to follow a given path based on the driving style. [257] built a personalized vehicle steering pattern to predict the driver's behavior and avoid vehicle collision. [258] proposed an efficiency desired path generation system by modeling the driver's personalized steering mode. [259] proposed a sinusoidal lane change kinematic model based on the driving style. It could adaptively adjust the related parameters according to individual driver behavior, to enhance the safety and comfort of the lane change assistance system. [260] presented a lane change decision model that could detect implicit maneuvers using a data-driven approach while satisfying the comfort and safety constraints.

4) DDT for Human-centric Shared Control: Highly automated driving will play an important until fully autonomous vehicles are developed. These systems will retain a human driver in the control loop. A shared-control system enables a human driver and an automation system to share control authority and cooperatively operate a vehicle [261–263]. However, one critical issue is identifying how to appropriately transfer and allocate the control authority [263–269]. [270] proposed a data-driven approach for estimating the driver's take-over readiness based purely on observable cues from in-vehicle vision sensors. [271] highlighted the importance of the personalized ADAS. It proposed a method to identify the competence and capacity of the driver and the ADAS that could be used to enhance the reliability, acceptance, and even the attractiveness of the system. [272] showed a personalized cooperative control system which could automatically adjust the related parameters based on the individual driving pattern, to make the assistance system easier to accept. [273, 274] proposed a collision probability-aware human–machine cooperative planning and tracking method by evaluating the risk level of the human driver's behavior; the system could be adaptively activated to incorporate the driver's intention and improve the automated vehicle's safety. [275] presented a human–machine adaptive shared control method to tackle automation performance degradation, wherein the control authority can be adaptively allocated by monitoring the driver state and automated vehicle performance. [276] created a shared control driver assistance system to avoid obstacles based on driving intention identification and situation assessment. Another method is that of inductive classification. It adopts an unlabeled data approach to recognize a human driver's driving intention and determine the desired maneuver based on the lateral offset and lateral velocity relative to the road center line. Three fuzzy controllers in different conditions determine the cooperative coefficient, which denotes the percentage of control authority resting with the controller and the human driver. To build the cooperative control framework for the human driver and the active rear steering system, the human driver model is established in [277] while taking into account different driving characteristics.

The goal of ADAS is to assist the driver in achieving a more intelligent, safe, and efficient driving experience. A wide range of personalities, sensitivities, and preferences have to be considered to ensure that all types of drivers are represented. A single driver can also have dynamically varying emotional states and abilities over time. Thus, the system should be personalized and adaptively cooperate with the driver to enhance user experience and make the ADAS easier to accept. Thus, ADAS-related studies need to not only focus on the specific modules and functions from a vehicular perspective but also consider the driver's personality, preferences, capabilities, etc. The proposed DDT provides a reasonable solution to address this requirement. The DDT system achieves this by leveraging the built unified model to optimize the ADAS module in terms of adaptability, predictability, and time-variable ability. Several studies reviewed in the previous section attempted to incorporate the driver's personality into the ADAS and, consequently, demonstrated its benefits. This encourages us to further investigate intelligent and personalized ADAS by leveraging the DDT system.

B. DDT in Personalized Human-Machine Interface

A human–machine interface (HMI) not only determines how good the user experience is, but also contributes to the trust-building process for drivers. A well-designed HMI requires the vehicle to adaptively recognize the driver's behavior and command, assess the driver's emotional state, and provide timely feedback [278]. Consequently, DDT effectively serves to improve the HMI for enhancing interaction efficiency and driver trust in the vehicle.

A typical area of interest in HMI is command recognition, which involves two widely studied tasks: activity and speech recognition. Hand gesture recognition is a commonly used activity recognition technique and has been implemented in several commercial vehicles [279–281]. In-vehicle hand gesture recognition enables the user to interact with the vehicle through static or dynamic gestures. The advancement of pattern recognition technology and intelligent hardware has popularized online hand gesture recognition. Significant breakthroughs in several aspects such as recognition accuracy, response time, computational memory consumption, user availability have contributed to this. According to one report [282],

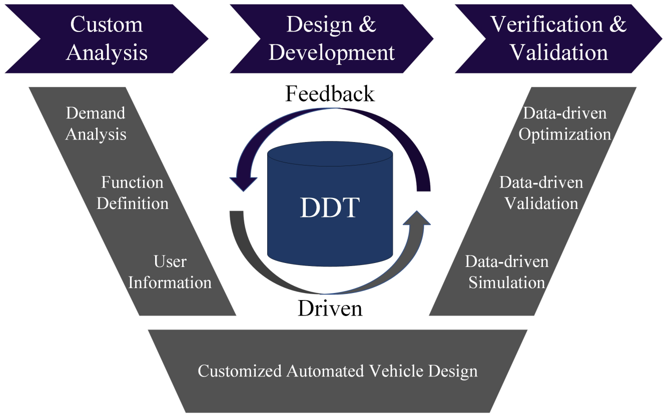

Fig. 9. DDT is utilized in the autonomous vehicle development.

speech control is expected to become the second most popular interface, and 80% of automobile man–machine interfaces will adopt speech control in the near future. Speech recognition has played a role in several applications such as automatic navigation, speech search, command input, and speech assistant. The use of the deep-learning capability of spoken dialogue system has been improved and has helped achieve impressive performances in audio processing applications. In addition, other modality interfaces, such as the brain control [283] and the haptic interface [284], have also been investigated. However, these approaches are currently limited to laboratory demonstrations and far from the practical deployment stage. Further investigation is required to integrate these approaches with other interfaces to achieve robust interaction.

Currently, most HMIs are designed using average modeling, wherein most functions are fixed for every driver. This means that unless users adapt to specific interaction gestures and pronunciations, the recognition accuracy will degrade. For instance, several real use-cases have demonstrated that speech recognition systems fail to handle diverse dialects, which hinders user experience. Thus, the HMI system should be able to adaptively tackle the diverse behavioral patterns and speech accents to improve the experience of end-users and make them feel like the system is customized. To accomplish this, the DDT can be utilized to fine-tune recognition models.

C. DDT in Automated Vehicle Development

Apart from enhancing the ADAS for a low-level autonomous driving system, the DDT can also be leveraged for high-level systems as shown in Fig. 9. These autonomous cars from the same factory or vehicle type were installed with the same decision algorithm and default configuration. The DDT system aids the autonomous vehicle in providing enhanced personalization and enables it to drive like a human, thereby enhancing passenger comfort and confidence. Furthermore, surrounding drivers can naturally interact with it and better understand its behavior and purpose. In addition, it can be used provide more reliable simulation systems for the development of autonomous vehicles. Validating the safety of autonomous vehicles in the real world is costly, dangerous, and time consuming [285]. Thus, performing this validation in simulated environments can help address these problems. However, the simulation of real and complex traffic scenarios is a challenging task owing to the highly dynamic nature of human behavior that results in diverse driving patterns. The DDT overcomes these challenges by providing diverse realistic driving models.

Several studies have introduced the human factor to autonomous driving systems [286]. For instance, [287] presented a proof-of-concept investigation to demonstrate that the autonomous driving design can be benefited from the cognitive work analysis. [288] presented an autonomous vehicle model based on dynamic human behavior. The model enabled vehicles to drive appropriately by mimicking the behavioral features of the driver. It achieved this by analyzing the drivers' characteristics such as gender, age, driving experience, personality, and emotion, thereby enabling personalization. [289] proposed a human-like autonomous car-following planning framework based on deep reinforcement learning. Human driving data were fed into a simulation environment to train the autonomous vehicle system to acquire human-like characteristics, thereby increasing the naturalism of its interactions with passengers and surrounding vehicles. [290] integrated social psychology tools into controller design for autonomous vehicles by predicting driver behavior and quantifying the driving style. The interactions between human and autonomous agents were modeled using game theory and the principle of best response. By studying certain common-yet-difficult traffic scenarios, they determined that autonomous performance can be significantly improved by incorporating the driver's behavior into the model. Owing to the intelligent transportation system comprising the human-vehicle-infrastructure-roadside units, [291, 292] introduced the parallel internet of vehicles concept, where the human factor is highlighted and modelled in the framework to flexibly adjust and allocate the available resources according to social acceptance.

Owing to the lack of real-world connected and autonomous vehicle (CAV) exposure data, evaluating the safety impacts of CAV has been a major challenge. Studies that attempt to simulate CAVs using a single simulation platform or by integrating multiple simulation platforms have limitations; in most cases, they consider only a small portion of a network and do not perform safety evaluations because of its inherent complexity [293]. [294] addressed this issue by constructing multiple solid human driver models based on real-world driving data. [295] utilized generative adversarial imitation learning to help representative human driver models learn and increase the realistic nature of the simulation. [296] proposed a driving training data rendering approach leveraging actual human-collected trajectories, which enhanced the ability of virtual agents within the previously unseen scenarios and situations. [297] presented a human-in-the-loop agent-based simulation that incorporated human crowd characteristics and behaviors to enhance the efficiency of crowd control for unmanned vehicles. They developed the individual path model by leveraging the social-force-based model to predict the near-future location of individuals for improving the path planning performance of the UV. To facilitate the visual intelligence testing of intelligent vehicles, [298] created a realistic artificial scenario simulator to generate synthetic images, and a virtual driving scenario dataset was developed, called ParallelEye-CS. Leveraging this simulator, [34] proposed a novel theoretical framework to address the long-tail problem using parallel technology. Here, a novel parallel vision actualization system (PVAS) capable of leveraging the constructed virtual parallel simulator was presented. It was used to search for challenging scenarios for improving the perception capability of autonomous vehicles. A similar concept was utilized in [299], which presented a virtual-real interactive point cloud generation framework for autonomous driving, called parallel point clouds (PPCs). To accelerate the evaluation and development of autonomous vehicles, [33] designed a human-in-the-loop parallel testing system to implement more challenging tests via virtual-real interaction. In these tests a human expert vaguely defined the tasks and performed qualitative judgments, following which the simulation system defined the tasks more precisely, generated further testing scenarios, and collected feedback from humans to validate the test results.

The DDT model can be utilized throughout the whole R&D process of autonomous vehicles in a data-driven manner from the custom analysis to the functional development and validation, and finally during on-road operation. Thus, the customization and personalization of the autonomous vehicles can be progressively achieved.

V. Observations and Recommendations

Existing driver modeling studies and DDT-related applications for multilevel autonomous vehicles were comprehensively reviewed. The various technologies and models proposed by these studies have been crucial in establishing DDT technology in the automotive industry; however, DDT has a considerable amount of untapped potential. However, numerous obstacles need to be overcome before DDT can become commercially viable. This section presents the opportunities and challenges that will govern the future research objectives in this domain.

A. Unified Modeling Framework

Driver modeling is the foundation of the successful operation of DDT systems. Existing driver models are based on isolated perspectives or individual parameters instead of being generalized. However, the driver's performance is multimodal and can have different physical or psychological reactions to different driving scenarios. Therefore, the first critical task in the implementation of DDT is to construct a practically viable unified digital model. However, the complexity of humans makes modeling and massive data fusion analysis challenging; in addition, the diversity of data sources, data variability, and heterogeneity present further obstacles [300]. A consensus should be reached on the framework of the DDT model and how to construct it based on the aggregated multimodal data trove. The corresponding algorithms and tools should be thoroughly investigated. Thus, the unified model of the DDT remains insufficiently defined and needs to be further explored and discussed.

B. Unsupervised Data Analysis

Data analysis relies on an intelligent method to recognize or detect specific states. Deep learning techniques are known for their powerful learning capability, and are currently the most popular approach in many applications [301–304]. However, deep learning-based methods require large datasets, which presents a challenge for the DDT system. In particular, a large multimodal corpus dataset of driver performance is yet to be developed. In addition to the effort of collecting data, unsupervised learning models are required for investigating approaches to tackle this challenge [305–308]. In addition, human driver performance is complex, diverse, and personalized. Therefore, building a dataset applicable to all scenarios is difficult. Thus, advanced unsupervised approaches should be further explored to overcome the lack of labeled data [309–313].

C. Multi-modal Sensor Fusion

A well-established DDT system is expected to involve multimodal fusion of massive volumes of data on various drivers, in addition to real-time, historical, virtual, and physical data. This requires multiple techniques including data cleaning, conversion, calibration, and mining, among others [314–318]. The related intelligent algorithm and method should be improved to handle the iteration and optimization of the massive data [319]. The corresponding connection and communication protocol is also crucial for the successful operation of the DDT system and needs to be standardized. Thus, multimodal data fusion should be carefully studied to support the efficient interaction between modules.

D. Regulation

In addition to new technologies, DDT comprises various regulatory aspects. To ensure wide applicability and feasibility of our research results, a wide variety of technical areas need to be considered. Furthermore, non-technical aspects including ethical issues, personal privacy, and the reliability of simulation outcomes, need to scrutinized when considering the utilization of DDT [320, 321]. Moreover, DDTs operate on heterogeneous data sources that must be protected by strong digital security and data governance policies to secure highly sensitive data; in addition, they must meet evolving legal/compliance requirements. To achieve this, we will need the cooperation of experts in various fields of research and technology, including social sciences, natural sciences, humanities, and other interdisciplinary fields.

E. Other Recommendations

The comprehensive digitization of the driver means that the DDT can be effectively merged and exchanged in cyberspace. This automatically enables the driver to temporarily acquire the driving skills of an expert and the ability to maintain control in risky scenarios. Furthermore, the DDT can be utilized to continuously mine potential requirements to generate novel, unique, and valuable product concepts, which can then be transformed into detailed customized products to cooperate with smart manufacturing. In addition, the vehicle design scheme continuously reduces the inconsistency between the vehicle's actual behavior and the design's expected behavior.

VI. Conclusion

Digitization is of utmost significance in the future in view of the development of advanced sensing and intelligent systems. Consequently, DT is potentially one of the most promising enabling technologies; it has already been introduced to several fields including intelligent vehicle and transportation systems. The driver, who remains indispensable to the system, must be incorporated with the other elements to form a complete driving H-CPS. However, systematic research into the digital human driver is rare. Therefore, this study proposes the concept of a DDT to introduce a more comprehensive model of the human driver. Compared with the original DT used in manufacturing, the DDT emphasizes the personality and capability of the driver instead of the external physiological-level state. Thus, it is expected to provide a theoretical basis for a human-centric intelligent driving system.

The DDT has significant potential for development considering the rapid growth of computing capacity, low-cost intelligent devices, data storage, convenient data acquisition, and AI. This study systematically illustrates the concept of the DDT and outlines its key enabling aspects. Current related technologies and applications have also been comprehensively reviewed. Furthermore, we have discussed how the DDT can be leveraged to further improve these technologies and applications. Unsettled technical issues and potential applications have also been presented. The proposed DDT is a work in progress that must be refined and allowed to evolve. In addition, several urgent issues must be addressed to increase its practical viability. For instance, a unified DDT modeling method based on multi-modal data is urgently required; the intelligent algorithms and data fusion approaches should be further investigated; and the corresponding regulations need to be established and followed. The DDT is expected to become a central research topic in the future as our ability to manipulate DT-enabled technology and our understanding of the human aspects in driving grows. In conclusion, this study aims to serve as a guide to peer researchers seeking to determine the future direction of DDT research and its possible applications.

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References

[1] M. Grieves, "Digital twin: manufacturing excellence through virtual factory replication," *White paper*, vol. 1, pp. 1–7, 2014.

[2] E. J. Tuegel, A. R. Ingraffea, T. G. Eason, and S. M. Spottswood, "Reengineering aircraft structural life prediction using a digital twin," *International Journal of Aerospace Engineering*, vol. 2011, 2011.

[3] E. Glaessgen and D. Stargel, "The digital twin paradigm for future nasa and us air force vehicles," in *53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference 14th AIAA*, 2012, p. 1818.

[4] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2405–2415, 2019.

[5] D. CeArley, B. Burke, S. Searle, and M. J. Walker, "Top 10 strategic technology trends for 2018," *The Top*, vol. 10, pp. 1–246, 2016.

[6] D. Cao, X. Wang, L. Li, C. Lv, X. Na, Y. Xing, X. Li, Y. Li, Y. Chen, and F. Wang, "Future directions of intelligent vehicles: Potentials, possibilities, and perspectives," *IEEE Transactions on Intelligent Vehicles*, vol. 7, no. 1, pp. 7–10, 2022.

[7] F.-Y. Wang, "Metavehicles in the metaverse: Moving to a new phase for intelligent vehicles and smart mobility," *IEEE Transactions on Intelligent Vehicles*, vol. 7, no. 1, pp. 1–5, 2022.

[8] Z.-X. Hu, Y. Wang, M.-F. Ge, and J. Liu, "Data-driven fault diagnosis method based on compressed sensing and improved multiscale network," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 4, pp. 3216–3225, 2020.

[9] J. Liu, Y. Hu, Y. Wang, B. Wu, J. Fan, and Z. Hu, "An integrated multi-sensor fusion-based deep feature learning approach for rotating machinery diagnosis," *Measurement Science and Technology*, vol. 29, no. 5, p. 055103, 2018.

[10] K. Zhou, C. Yang, J. Liu, and Q. Xu, "Dynamic graph-based feature learning with few edges considering noisy samples for rotating machinery fault diagnosis," *IEEE Transactions on Industrial Electronics*, pp. 1–1, 2021.

[11] Z. Wang, X. Liao, X. Zhao, K. Han, P. Tiwari, M. J. Barth, and G. Wu, "A digital twin paradigm: Vehicle-to-cloud based advanced driver assistance systems," in *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*, 2020, pp. 1–6.

[12] X. Liao, Z. Wang, X. Zhao, K. Han, P. Tiwari, M. J. Barth, and G. Wu, "Cooperative ramp merging design and field implementation: A digital twin approach based on vehicle-to-cloud communication," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–11, 2021.

[13] G. Bhatti, H. Mohan, and R. R. Singh, "Towards the future of ssmart electric vehicles: Digital twin technology," *Renewable and Sustainable Energy Reviews*, vol. 141, p. 110801, 2021.

[14] J. Li, H. Cheng, H. Guo, and S. Qiu, "Survey on artificial intelligence for vehicles," *Automotive Innovation*, vol. 1, no. 1, pp. 2–14, 2018.

[15] D. Zhang, C. Lv, T. Yang, and P. Hang, "Cyber-attack detection for autonomous driving using vehicle dynamic state estimation," *Automotive Innovation*, vol. 4, no. 3, pp. 262–273, 2021.

[16] Y. Liu, K. Zhang, and Z. Li, "Application of digital twin and parallel system in automated driving testing," in *2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI)*, 2021, pp. 123–126.

[17] M. Farsi, A. Daneshkhah, A. Hosseinian-Far, H. Jahankhani *et al.*, *Digital twin technologies and smart cities*. Springer, 2020.

[18] M. González, O. Salgado, J. Croes, B. Pluymers, and W. Desmet, "A digital twin for operational evaluation of vertical transportation systems," *IEEE Access*, vol. 8, pp. 114 389–114 400, 2020.

[19] D. N. Ford and C. M. Wolf, "Smart cities with digital twin systems for disaster management," *Journal of management in engineering*, vol. 36, no. 4, p. 04020027, 2020.

[20] F.-Y. Wang, X. Wang, L. Li, and L. Li, "Steps toward parallel intelligence," *IEEE/CAA Journal of Automatica Sinica*, vol. 3, no. 4, pp. 345–348, 2016.

[21] X. Wang, L. Li, Y. Yuan, P. Ye, and F.-Y. Wang, "Acp-based social computing and parallel intelligence: Societies 5.0 and beyond," *CAAI Transactions on Intelligence Technology*, vol. 1, no. 4, pp. 377–393, 2016.

[22] D. Gelernter, *Mirror worlds: Or the day software puts the universe in a shoebox... How it will happen and what it will mean*. Oxford University Press, 1993.

[23] F. Wang, "Shadow systems: a new concept for nested and embedded co-simulation for intelligent systems," *Tucson, Arizona State, USA: University of Arizona*, 1994.

[24] A. Villalonga, G. Beruvides, F. Castano, and R. E. Haber, "Cloud-based industrial cyber–physical system for data-driven reasoning: A review and use case on an industry 4.0 pilot line," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 9, pp. 5975–5984, 2020.

[25] C. Lv, X. Hu, A. Sangiovanni-Vincentelli, Y. Li, C. M. Martinez, and D. Cao, "Driving-style-based codesign optimization of an automated electric vehicle: A cyber-physical system approach," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 4, pp. 2965–2975, 2018.

[26] C. Lv, Y. Xing, J. Zhang, X. Na, Y. Li, T. Liu, D. Cao, and F.-Y. Wang, "Levenberg–marquardt backpropagation training of multilayer

neural networks for state estimation of a safety-critical cyber-physical system," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 8, pp. 3436–3446, 2017.

[27] U. N. S. Foundation, "Cyber-physical systems (cps)," no. 08-611, 2008.

[28] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for industry 4.0-based manufacturing systems," *Manufacturing letters*, vol. 3, pp. 18–23, 2015.

[29] P. J. Mosterman and J. Zander, "Industry 4.0 as a cyber-physical system study," *Software & Systems Modeling*, vol. 15, no. 1, pp. 17–29, 2016.

[30] F.-Y. Wang, N.-N. Zheng, D. Cao, C. M. Martinez, L. Li, and T. Liu, "Parallel driving in cpss: a unified approach for transport automation and vehicle intelligence," *IEEE/CAA Journal of Automatica Sinica*, vol. 4, no. 4, pp. 577–587, 2017.

[31] J. J. Zhang, F.-Y. Wang, X. Wang, G. Xiong, F. Zhu, Y. Lv, J. Hou, S. Han, Y. Yuan, Q. Lu *et al.*, "Cyber-physical-social systems: The state of the art and perspectives," *IEEE Transactions on Computational Social Systems*, vol. 5, no. 3, pp. 829–840, 2018.

[32] F.-Y. Wang, "Parallel control and management for intelligent transportation systems: Concepts, architectures, and applications," *IEEE Transactions on Intelligent Transportation Systems*, vol. 11, no. 3, pp. 630–638, 2010.

[33] L. Li, X. Wang, K. Wang, Y. Lin, J. Xin, L. Chen, L. Xu, B. Tian, Y. Ai, J. Wang *et al.*, "Parallel testing of vehicle intelligence via virtual-real interaction," *Science robotics*, 2019.

[34] J. Wang, X. Wang, T. Shen, Y. Wang, L. Li, Y. Tian, H. Yu, L. Chen, J. Xin, X. Wu *et al.*, "Parallel vision for long-tail regularization: initial results from ivfc autonomous driving testing," *IEEE Transactions on Intelligent Vehicles*, 2022.

[35] Y. Xing, C. Lv, L. Chen, H. Wang, H. Wang, D. Cao, E. Velenis, and F.-Y. Wang, "Advances in vision-based lane detection: Algorithms, integration, assessment, and perspectives on acp-based parallel vision," *IEEE/CAA Journal of Automatica Sinica*, vol. 5, no. 3, pp. 645–661, 2018.

[36] F. Vanderhaegen, "Risk analysis from the concept of dissonnance to identify the gaps from design and usage of automated systems," in *H-CPS-I: Human Cyber Physical System Interaction-Control for the Human Welfare*, 2014.

[37] P. of CPHS 2016, "1st ifac conference on cyber-physical & human-systems," *IFAC-PapersOnLine*, vol. 49, pp. 1–252, 2016.

[38] J. Zhou, Y. Zhou, B. Wang, and J. Zang, "Human–cyber–physical systems (hcpss) in the context of new-generation intelligent manufacturing," *Engineering*, vol. 5, no. 4, pp. 624–636, 2019.

[39] Z. Liu and J. Wang, "Human-cyber-physical systems: concepts, challenges, and research opportunities," *Frontiers of Information Technology & Electronic Engineering*, vol. 21, no. 11, pp. 1535–1553, 2020.

[40] T. Feng, F. Fan, and T. Bednarz, "A review of computer graphics approaches to urban modeling from a machine learning perspective," *Frontiers of Information Technology & Electronic Engineering*, vol. 22, no. 7, pp. 915–925, 2021.

[41] Y. Wang, K. Zheng, D. Tian, X. Duan, and J. Zhou, "Pre-training with asynchronous supervised learning for reinforcement learning based autonomous driving," *Frontiers of Information Technology & Electronic Engineering*, vol. 22, no. 5, pp. 673–686, 2021.

[42] C. Wu and T. Zhang, "Intelligent unmanned systems: important achievements and applications of new generation artificial intelligence," pp. 649–651, 2020.

[43] M. Al-Sharman, D. Murdoch, D. Cao, C. Lv, Y. Zweiri, D. Rayside, and W. Melek, "A sensorless state estimation for a safety-oriented cyber-physical system in urban driving: Deep learning approach," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 1, pp. 169–178, 2021.

[44] B. Liu, Y.-r. Zhang, X.-l. Cao, Y. Liu, B. Gu, and T.-x. Wang, "A survey of model-driven techniques and tools for cyber-physical systems," *Frontiers of Information Technology & Electronic Engineering*, vol. 21, no. 11, pp. 1567–1590, 2020.

[45] M.-r. Xiao, Y.-w. Dong, Q.-w. Gou, F. Xue, and Y.-h. Chen, "Architecture-level particular risk modeling and analysis for a cyber-physical system with aadl," *Frontiers of Information Technology & Electronic Engineering*, vol. 21, no. 11, pp. 1607–1625, 2020.

[46] J. Corral-Acero, F. Margara, M. Marciniak, C. Rodero, F. Loncaric, Y. Feng, A. Gilbert, J. F. Fernandes, H. A. Bukhari, A. Wajdan *et al.*, "The 'digital twin'to enable the vision of precision cardiology," *European heart journal*, vol. 41, no. 48, pp. 4556–4564, 2020.

[47] J. I. Jimenez, H. Jahankhani, and S. Kendzierskyj, "Health care in the cyberspace: Medical cyber-physical system and digital twin challenges," in *Digital twin technologies and smart cities*. Springer, 2020, pp. 79–92.

[48] R. Portela, C. Varsakelis, A. Richelle, N. Giannelos, J. Pence, S. Dessoy, and M. v. Stosch, "When is an in silico representation a digital twin? a biopharmaceutical industry approach to the digital twin concept," in *Digital Twins*. Springer, 2020, pp. 35–55.

[49] B. R. Barricelli, E. Casiraghi, J. Gliozzo, A. Petrini, and S. Valtolina, "Human digital twin for fitness management," *Ieee Access*, vol. 8, pp. 26 637–26 664, 2020.

[50] B. Wang, H. Zhou, G. Yang, X. Li, and H. Yang, "Human digital twin (hdt) driven human-cyber-physical systems: Key technologies and applications," *Chinese Journal of Mechanical Engineering*, vol. 35, no. 1, pp. 1–6, 2022.

[51] G. Sikander and S. Anwar, "Driver fatigue detection systems: A review," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 6, pp. 2339–2352, 2019.

[52] A. Němcová, V. Svozilová, K. Bucsuházy, R. Smíšek, M. Mézl, B. Hesko, M. Belák, M. Bilík, P. Maxera, M. Seitl, T. Dominik, M. Semela, M. Šucha, and R. Kolář, "Multimodal features for detection of driver stress and fatigue: Review," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 6, pp. 3214–3233, 2021.

[53] C. Zhang and A. Eskandarian, "A survey and tutorial of eeg-based brain monitoring for driver state analysis," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 7, pp. 1222–1242, 2021.

[54] C. Gou, Y. Zhou, Y. Xiao, X. Wang, and H. Yu, "Cascade learning for driver facial monitoring," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2022.

[55] Q. Deng and D. Soffker, "A review of hmm-based approaches of driving behaviors recognition and prediction," *IEEE Transactions on Intelligent Vehicles*, vol. 7, no. 1, pp. 21–31, 2022.

[56] A. Paul, R. Chauhan, R. Srivastava, and M. Baruah, "Advanced driver assistance systems," SAE Technical Paper, Tech. Rep., 2016.

[57] J. Nidamanuri, C. Nibhanupudi, R. Assfalg, and H. Venkataraman, "A progressive review - emerging technologies for adas driven solutions," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2021.

[58] M. Marcano, S. Díaz, J. Pérez, and E. Irigoyen, "A review of shared control for automated vehicles: Theory and applications," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 6, pp. 475–491, 2020.

[59] M. Hasenjäger, M. Heckmann, and H. Wersing, "A survey of personalization for advanced driver assistance systems," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 2, pp. 335–344, 2020.

[60] D. Yi, J. Su, L. Hu, C. Liu, M. Quddus, M. Dianati, and W.-H. Chen, "Implicit personalization in driving assistance: State-of-the-art and open issues," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 3, pp. 397–413, 2020.

[61] C. Bila, F. Sivrikaya, M. A. Khan, and S. Albayrak, "Vehicles of the future: A survey of research on safety issues," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 5, pp. 1046–1065, 2017.

[62] H. Zhang, B. Xin, L.-h. Dou, J. Chen, and K. Hirota, "A review of cooperative path planning of an unmanned aerial vehicle group," *Frontiers of Information Technology & Electronic Engineering*, vol. 21, no. 12, pp. 1671–1694, 2020.

[63] P. S. Lavieri and C. R. Bhat, "Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future," *Transportation research part A: policy and practice*, vol. 124, pp. 242–261, 2019.

[64] M. Boban, A. Kousaridas, K. Manolakis, J. Eichinger, and W. Xu, "Connected roads of the future: Use cases, requirements, and design considerations for vehicle-to-everything communications," *IEEE Vehicular Technology Magazine*, vol. 13, no. 3, pp. 110–123, 2018.

[65] Y. F. Payalan and M. A. Guvensan, "Towards next-generation vehicles featuring the vehicle intelligence," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 1, pp. 30–47, 2020.

[66] A. E. Mekki, A. Bouhoute, and I. Berrada, "Improving driver identification for the next-generation of in-vehicle software systems," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 8, pp. 7406–7415, 2019.

[67] P. Hang, C. Huang, Z. Hu, and C. Lv, "Driving conflict resolution of autonomous vehicles at unsignalized intersections: A differential game approach," *IEEE/ASME Transactions on Mechatronics*, 2022.

[68] J. Wu, Z. Huang, W. Huang, and C. Lv, "Prioritized experience-based reinforcement learning with human guidance for autonomous driving," *IEEE Transactions on Neural Networks and Learning Systems*, 2022.

[69] P. Hang, C. Huang, Z. Hu, Y. Xing, and C. Lv, "Decision making of connected automated vehicles at an unsignalized roundabout considering personalized driving behaviours," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 5, pp. 4051–4064, 2021.

[70] S. O.-R. A. V. S. Committee *et al.*, "Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems," *SAE Standard J*, vol. 3016, pp. 1–16, 2014.

[71] Z. Hu, Y. Zhang, Q. Li, and C. Lv, "Human–machine telecollaboration accelerates the safe deployment of large-scale autonomous robots during the covid-19 pandemic," *Frontiers in Robotics and AI*, p. 104, 2022.

[72] J. Wu, Z. Huang, Z. Hu, and C. Lv, "Toward human-in-the-loop ai: Enhancing deep reinforcement learning via real-time human guidance for autonomous driving," *Engineering*, 2022.

[73] P. A. Hancock, *Mind, machine and morality: Toward a philosophy of human-technology symbiosis*. CRC Press, 2017.

[74] Y. Xing, C. Lv, D. Cao, and P. Hang, "Toward human-vehicle collaboration: Review and perspectives on human-centered collaborative automated driving," *Transportation Research Part C: Emerging Technologies*, vol. 128, p. 103199, 2021.

[75] S. Shah, D. Dey, C. Lovett, and A. Kapoor, "Airsim: High-fidelity visual and physical simulation for autonomous vehicles," in *Field and service robotics*. Springer, 2018, pp. 621–635.

[76] A. Kashevnik, R. Shchedrin, C. Kaiser, and A. Stocker, "Driver distraction detection methods: A literature review and framework," *IEEE Access*, vol. 9, pp. 60 063–60 076, 2021.

[77] S. Poria, E. Cambria, R. Bajpai, and A. Hussain, "A review of affective computing: From unimodal analysis to multimodal fusion," *Information Fusion*, vol. 37, pp. 98–125, 2017.

[78] Z. Tu, W. Xie, Q. Qin, R. Poppe, R. C. Veltkamp, B. Li, and J. Yuan, "Multi-stream cnn: Learning representations based on human-related regions for action recognition," *Pattern Recognition*, vol. 79, pp. 32–43, 2018.

[79] S. Chennupati, G. Sistu, S. Yogamani, and S. A Rawashdeh, "Multinet++: Multi-stream feature aggregation and geometric loss strategy for multi-task learning," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 2019, pp. 0–0.

[80] I. Ahmad, R. M. Noor, Z. Ahmed, N. Akram, F. P. García Márquez *et al.*, "A cooperative heterogeneous vehicular clustering framework for efficiency improvement," *Frontiers of Information Technology & Electronic Engineering*, vol. 22, no. 9, pp. 1247–1259, 2021.

[81] Y.-p. Wang, K.-x. Zheng, D.-x. Tian, X.-t. Duan, and J.-s. Zhou, "Cooperative channel assignment for vanets based on multiagent reinforcement learning," *Frontiers of Information Technology & Electronic Engineering*, vol. 21, no. 7, pp. 1047–1058, 2020.

[82] W. Hong, G. Yue, X. Ge, and H. Wang, "High-throughput millimeter-wave wireless communications," *Frontiers of Information Technology & Electronic Engineering*, vol. 22, no. 4, pp. 437–440, 2021.

[83] I. Ahmad, X. Ge, and Q.-L. Han, "Decentralized dynamic event-triggered communication and active suspension control of in-wheel motor driven electric vehicles with dynamic damping," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 5, pp. 971–986, 2021.

[84] Z. Yi, W. Zou, and X. Sun, "Prior information based channel estimation for millimeter-wave massive mimo vehicular communications in 5g and beyond," *Frontiers of Information Technology & Electronic Engineering*, vol. 22, no. 6, pp. 777–789, 2021.

[85] J.-h. Zhang, P. Tang, L. Yu, T. Jiang, and L. Tian, "Channel measurements and models for 6g: current status and future outlook," *Frontiers of information technology & electronic engineering*, vol. 21, no. 1, pp. 39–61, 2020.

[86] T. B. R. Company, "Driver monitoring systems global market report 2021: Covid-19 growth and change to 2030," The Business Research Company, Tech. Rep., 2021.

[87] H. M. Eraqi, Y. Abouelnaga, M. H. Saad, and M. N. Moustafa, "Driver distraction identification with an ensemble of convolutional neural networks," *Journal of Advanced Transportation*, vol. 2019, 2019.

[88] B. Baheti, S. Talbar, and S. Gajre, "Towards computationally efficient and realtime distracted driver detection with mobilevgg network," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 4, pp. 565–574, 2020.

[89] C.-Y. Chiou, W.-C. Wang, S.-C. Lu, C.-R. Huang, P.-C. Chung, and Y.-Y. Lai, "Driver monitoring using sparse representation with part-based temporal face descriptors," *IEEE transactions on intelligent transportation systems*, vol. 21, no. 1, pp. 346–361, 2019.

[90] A. Fasanmade, Y. He, A. H. Al-Bayatti, J. N. Morden, S. O. Aliyu, A. S. Alfakeeh, and A. O. Alsayed, "A fuzzy-logic approach to dynamic bayesian severity level classification of driver distraction using image recognition," *IEEE Access*, vol. 8, pp. 95 197–95 207, 2020.

[91] A. Rangesh and M. M. Trivedi, "When vehicles ¡italic¿see¡/italic¿ pedestrians with phones: A multicue framework for recognizing phone-based activities of pedestrians," *IEEE Transactions on Intelligent Vehicles*, vol. 3, no. 2, pp. 218–227, 2018.

[92] C. Ou and F. Karray, "Enhancing driver distraction recognition using generative adversarial networks," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 3, pp. 385–396, 2020.

[93] Z. Hu, Y. Xing, W. Gu, D. Cao, and C. Lv, "Driver anomaly quantification for intelligent vehicles: A contrastive learning approach with representation clustering," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2022.

[94] Z. Hu, Y. Xing, C. Lv, P. Hang, and J. Liu, "Deep convolutional neural network-based bernoulli heatmap for head pose estimation," *Neurocomputing*, vol. 436, pp. 198–209, 2021.

[95] Z. Hu, Y. Zhang, Y. Xing, Y. Zhao, D. Cao, and C. Lv, "Toward human-centered automated driving: A novel spatiotemporal vision transformer-enabled head tracker," *IEEE Vehicular Technology Magazine*, pp. 2–9, 2022.

[96] A. Tawari, S. Martin, and M. M. Trivedi, "Continuous head movement estimator for driver assistance: Issues, algorithms, and on-road evaluations," *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 2, pp. 818–830, 2014.

[97] R. Oyini Mbouna, S. G. Kong, and M.-G. Chun, "Visual analysis of eye state and head pose for driver alertness monitoring," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 3, pp. 1462–1469, 2013.

[98] L. Yekhshatyan and J. D. Lee, "Changes in the correlation between eye and steering movements indicate driver distraction," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 1, pp. 136–145, 2013.

[99] Z. Li, S. Bao, I. V. Kolmanovsky, and X. Yin, "Visual-manual distraction detection using driving performance indicators with naturalistic driving data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 8, pp. 2528–2535, 2018.

[100] P. Jiménez, L. M. Bergasa, J. Nuevo, N. Hernández, and I. G. Daza, "Gaze fixation system for the evaluation of driver distractions induced by ivis," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 3, pp. 1167–1178, 2012.

[101] S. Vora, A. Rangesh, and M. M. Trivedi, "Driver gaze zone estimation using convolutional neural networks: A general framework and ablative analysis," *IEEE Transactions on Intelligent Vehicles*, vol. 3, no. 3, pp. 254–265, 2018.

[102] M. Lundgren, L. Hammarstrand, and T. McKelvey, "Driver-gaze zone estimation using bayesian filtering and gaussian processes," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 10, pp. 2739–2750, 2016.

[103] L. Fridman, P. Langhans, J. Lee, and B. Reimer, "Driver gaze region estimation without use of eye movement," *IEEE Intelligent Systems*, vol. 31, no. 3, pp. 49–56, 2016.

[104] G. Li and W.-Y. Chung, "Combined eeg-gyroscope-tdcs brain machine interface system for early management of driver drowsiness," *IEEE Transactions on Human-Machine Systems*, vol. 48, no. 1, pp. 50–62, 2018.

[105] S. Wang, Y. Zhang, C. Wu, F. Darvas, and W. A. Chaovalitwongse, "Online prediction of driver distraction based on brain activity patterns," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 1, pp. 136–150, 2015.

[106] Y.-K. Wang, T.-P. Jung, and C.-T. Lin, "Eeg-based attention tracking during distracted driving," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 23, no. 6, pp. 1085–1094, 2015.

[107] Y. Xing, C. Lv, H. Wang, D. Cao, E. Velenis, and F.-Y. Wang, "Driver activity recognition for intelligent vehicles: A deep learning approach," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 6, pp. 5379–5390, 2019.

[108] Y. Xing, C. Lv, Z. Zhang, H. Wang, X. Na, D. Cao, E. Velenis, and F.-Y. Wang, "Identification and analysis of driver postures for in-vehicle driving activities and secondary tasks recognition," *IEEE Transactions on Computational Social Systems*, vol. 5, no. 1, pp. 95–108, 2018.

[109] F. Sajid, A. R. Javed, A. Basharat, N. Kryvinska, A. Afzal, and M. Rizwan, "An efficient deep learning framework for distracted driver detection," *IEEE Access*, vol. 9, pp. 169 270–169 280, 2021.

[110] T. Billah, S. M. M. Rahman, M. O. Ahmad, and M. N. S. Swamy, "Recognizing distractions for assistive driving by tracking body parts," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 29, no. 4, pp. 1048–1062, 2019.

[111] I. Jegham, A. B. Khalifa, I. Alouani, and M. A. Mahjoub, "Soft spatial attention-based multimodal driver action recognition using deep learning," *IEEE Sensors Journal*, vol. 21, no. 2, pp. 1918–1925, 2021.

[112] S. Venugopalan, M. Rohrbach, J. Donahue, R. Mooney, T. Darrell, and K. Saenko, "Sequence to sequence-video to text," in *Proceedings of the IEEE international conference on computer vision*, 2015, pp. 4534–4542.

[113] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, "A simple framework for contrastive learning of visual representations," in *International*

conference on machine learning. PMLR, 2020, pp. 1597–1607.

[114] S. Han, H. Mao, and W. J. Dally, "Deep compression: Compressing deep neural networks with pruning, trained quantization and huffman coding," *arXiv preprint arXiv:1510.00149*, 2015.

[115] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, "Squeezenet: Alexnet-level accuracy with 50x fewer parameters and¡ 0.5 mb model size," *arXiv preprint arXiv:1602.07360*, 2016.

[116] K. Stojmenova and J. Sodnik, "Detection-response task—uses and limitations," *Sensors*, vol. 18, no. 2, p. 594, 2018.

[117] M. Gjoreski, M. Z. Gams, M. Lustrek, P. Genc, J.-U. Garbas, and T. Hassan, "Machine learning and end-to-end deep learning for monitoring driver distractions from physiological and visual signals," *IEEE Access*, vol. 8, pp. 70 590–70 603, 2020.

[118] O. Dehzangi, V. Sahu, M. Taherisadr, and S. Galster, "Multi-modal system to detect on-the-road driver distraction," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 2191–2196.

[119] X. Wang, Y. Zhu, S. Han, L. Yang, H. Gu, and F.-Y. Wang, "Fast and progressive misbehavior detection in internet of vehicles based on broad learning and incremental learning systems," *IEEE Internet of Things Journal*, 2021.

[120] Y. Xie, Y. L. Murphey, and D. S. Kochhar, "Personalized driver workload estimation using deep neural network learning from physiological and vehicle signals," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 3, pp. 439–448, 2020.

[121] A. Kashevnik, I. Lashkov, A. Ponomarev, N. Teslya, and A. Gurtov, "Cloud-based driver monitoring system using a smartphone," *IEEE Sensors Journal*, vol. 20, no. 12, pp. 6701–6715, 2020.

[122] S. Kanarachos, S.-R. G. Christopoulos, and A. Chroneos, "Smartphones as an integrated platform for monitoring driver behaviour: The role of sensor fusion and connectivity," *Transportation research part C: emerging technologies*, vol. 95, pp. 867–882, 2018.

[123] A. U. Nambi, S. Bannur, I. Mehta, H. Kalra, A. Virmani, V. N. Padmanabhan, R. Bhandari, and B. Raman, "Hams: Driver and driving monitoring using a smartphone," in *Proceedings of the 24th Annual International Conference on Mobile Computing and Networking*, 2018, pp. 840–842.

[124] K. Ben Ahmed, B. Goel, P. Bharti, S. Chellappan, and M. Bouhorma, "Leveraging smartphone sensors to detect distracted driving activities," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 9, pp. 3303–3312, 2019.

[125] Z. Hu, C. Lv, P. Hang, C. Huang, and Y. Xing, "Data-driven estimation of driver attention using calibration-free eye gaze and scene features," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 2, pp. 1800–1808, 2022.

[126] S. Jha and C. Busso, "Estimation of driver's gaze region from head position and orientation using probabilistic confidence regions," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2022.

[127] R. F. Ribeiro and P. D. P. Costa, "Driver gaze zone dataset with depth data," in *2019 14th IEEE International Conference on Automatic Face Gesture Recognition (FG 2019)*, 2019, pp. 1–5.

[128] S. Ghosh, A. Dhall, G. Sharma, S. Gupta, and N. Sebe, "Speak2label: Using domain knowledge for creating a large scale driver gaze zone estimation dataset," in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV) Workshops*, October 2021, pp. 2896–2905.

[129] M. Selim, A. Firintepe, A. Pagani, and D. Stricker, "Autopose: Large-scale automotive driver head pose and gaze dataset with deep head orientation baseline." in *VISIGRAPP (4: VISAPP)*, 2020, pp. 599–606.

[130] S. Jha, M. F. Marzban, T. Hu, M. H. Mahmoud, N. Al-Dhahir, and C. Busso, "The multimodal driver monitoring database: A naturalistic corpus to study driver attention," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–17, 2021.

[131] J. M. Ramírez, M. D. Rodríguez, A. G. Andrade, L. A. Castro, J. Beltrán, and J. S. Armenta, "Inferring drivers' visual focus attention through head-mounted inertial sensors," *IEEE Access*, vol. 7, pp. 185 422–185 432, 2019.

[132] A. Palazzi, D. Abati, S. Calderara, F. Solera, and R. Cucchiara, "Predicting the driver's focus of attention: the dr(eye)ve project," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2018.

[133] Y. Xia, D. Zhang, J. Kim, K. Nakayama, K. Zipser, and D. Whitney, "Predicting driver attention in critical situations," in *Asian conference on computer vision*. Springer, 2018, pp. 658–674.

[134] J. Fang, D. Yan, J. Qiao, and J. Xue, "Dada: A large-scale benchmark and model for driver attention prediction in accidental scenarios," *arXiv preprint arXiv:1912.12148*, 2019.

[135] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *International Conference on Medical image computing and computer-assisted intervention*. Springer, 2015, pp. 234–241.

[136] Y. Xing, C. Lv, H. Wang, H. Wang, Y. Ai, D. Cao, E. Velenis, and F.-Y. Wang, "Driver lane change intention inference for intelligent vehicles: Framework, survey, and challenges," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 5, pp. 4377–4390, 2019.

[137] Y. Xing, C. Lv, H. Wang, D. Cao, and E. Velenis, "An ensemble deep learning approach for driver lane change intention inference," *Transportation Research Part C: Emerging Technologies*, vol. 115, p. 102615, 2020.

[138] F. Bocklisch, S. F. Bocklisch, M. Beggiato, and J. F. Krems, "Adaptive fuzzy pattern classification for the online detection of driver lane change intention," *Neurocomputing*, vol. 262, pp. 148–158, 2017.

[139] S. Wang, X. Zhao, Q. Yu, and T. Yuan, "Identification of driver braking intention based on long short-term memory (lstm) network," *IEEE Access*, vol. 8, pp. 180 422–180 432, 2020.

[140] L. G. Hernández-Rojas, E. Martínez, and J. M. Antelis, "Detection of emergency braking intention using driver's electroencephalographic signals," *IEEE Latin America Transactions*, vol. 17, no. 01, pp. 111–118, 2019.

[141] T. Teng, L. Bi, and Y. Liu, "Eeg-based detection of driver emergency braking intention for brain-controlled vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 6, pp. 1766–1773, 2018.

[142] A. Bisoffi, F. Biral, M. Da Lio, and L. Zaccarian, "Longitudinal jerk estimation of driver intentions for advanced driver assistance systems," *IEEE/ASME Transactions on Mechatronics*, vol. 22, no. 4, pp. 1531–1541, 2017.

[143] X. He, H. Yang, Z. Hu, and C. Lv, "Robust lane change decision making for autonomous vehicles: An observation adversarial reinforcement learning approach," *IEEE Transactions on Intelligent Vehicles*, 2022.

[144] Y. Zhang, Q. Lin, J. Wang, S. Verwer, and J. M. Dolan, "Lane-change intention estimation for car-following control in autonomous driving," *IEEE Transactions on Intelligent Vehicles*, vol. 3, no. 3, pp. 276–286, 2018.

[145] L. Tang, H. Wang, W. Zhang, Z. Mei, and L. Li, "Driver lane change intention recognition of intelligent vehicle based on long short-term memory network," *IEEE Access*, vol. 8, pp. 136 898–136 905, 2020.

[146] L. Li, W. Zhao, C. Xu, C. Wang, Q. Chen, and S. Dai, "Lane-change intention inference based on rnn for autonomous driving on highways," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 6, pp. 5499–5510, 2021.

[147] A. Zyner, S. Worrall, and E. Nebot, "A recurrent neural network solution for predicting driver intention at unsignalized intersections," *IEEE Robotics and Automation Letters*, vol. 3, no. 3, pp. 1759–1764, 2018.

[148] T. Rehder, A. Koenig, M. Goehl, L. Louis, and D. Schramm, "Lane change intention awareness for assisted and automated driving on highways," *IEEE Transactions on Intelligent Vehicles*, vol. 4, no. 2, pp. 265–276, 2019.

[149] A. Zyner, S. Worrall, and E. Nebot, "Naturalistic driver intention and path prediction using recurrent neural networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 4, pp. 1584–1594, 2020.

[150] Q. Chen, W. Zhao, C. Xu, C. Wang, L. Li, and S. Dai, "An improved iohmm-based stochastic driver lane-changing model," *IEEE Transactions on Human-Machine Systems*, vol. 51, no. 3, pp. 211–220, 2021.

[151] A. Doshi and M. M. Trivedi, "On the roles of eye gaze and head dynamics in predicting driver's intent to change lanes," *IEEE Transactions on Intelligent Transportation Systems*, vol. 10, no. 3, pp. 453–462, 2009.

[152] A. Doshi, B. Morris, and M. Trivedi, "On-road prediction of driver's intent with multimodal sensory cues," *IEEE Pervasive Computing*, vol. 10, no. 3, pp. 22–34, 2011.

[153] G. Xu, L. Liu, and Z. Song, "Driver behavior analysis based on bayesian network and multiple classifiers," in *2010 IEEE International Conference on Intelligent Computing and Intelligent Systems*, vol. 3, 2010, pp. 663–668.

[154] F. Lethaus, M. R. Baumann, F. Köster, and K. Lemmer, "A comparison of selected simple supervised learning algorithms to predict driver intent based on gaze data," *Neurocomputing*, vol. 121, pp. 108–130, 2013.

[155] M. Liebner, M. Baumann, F. Klanner, and C. Stiller, "Driver intent inference at urban intersections using the intelligent driver model," in *2012 IEEE Intelligent Vehicles Symposium*, 2012, pp. 1162–1167.

[156] E. Ohn-Bar, A. Tawari, S. Martin, and M. M. Trivedi, "Predicting driver maneuvers by learning holistic features," in *2014 IEEE Intelligent*

Vehicles Symposium Proceedings, 2014, pp. 719–724.
[157] D. Windridge, A. Shaukat, and E. Hollnagel, "Characterizing driver intention via hierarchical perception–action modeling," *IEEE Transactions on Human-Machine Systems*, vol. 43, no. 1, pp. 17–31, 2013.
[158] Y. Xing, C. Lv, Y. Liu, Y. Zhao, D. Cao, and S. Kawahara, "Hybrid-learning-based driver steering intention prediction using neuromuscular dynamics," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 2, pp. 1750–1761, 2022.
[159] D. Yi, J. Su, C. Liu, and W.-H. Chen, "Trajectory clustering aided personalized driver intention prediction for intelligent vehicles," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 6, pp. 3693–3702, 2019.
[160] C. Wang, F. Li, Y. Wang, and J. R. Wagner, "Haptic assistive control with learning-based driver intent recognition for semi-autonomous vehicles," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2021.
[161] J. Yu, S. Park, S. Lee, and M. Jeon, "Driver drowsiness detection using condition-adaptive representation learning framework," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 11, pp. 4206–4218, 2019.
[162] B.-G. Lee and W.-Y. Chung, "Driver alertness monitoring using fusion of facial features and bio-signals," *IEEE Sensors Journal*, vol. 12, no. 7, pp. 2416–2422, 2012.
[163] G. Li and W.-Y. Chung, "Detection of driver drowsiness using wavelet analysis of heart rate variability and a support vector machine classifier," *Sensors*, vol. 13, no. 12, pp. 16 494–16 511, 2013.
[164] S.-J. Jung, H.-S. Shin, and W.-Y. Chung, "Driver fatigue and drowsiness monitoring system with embedded electrocardiogram sensor on steering wheel," *IET Intelligent Transport Systems*, vol. 8, no. 1, pp. 43–50, 2014.
[165] Z. Li, S. E. Li, R. Li, B. Cheng, and J. Shi, "Online detection of driver fatigue using steering wheel angles for real driving conditions," *Sensors*, vol. 17, no. 3, p. 495, 2017.
[166] J. H. Yang, Z.-H. Mao, L. Tijerina, T. Pilutti, J. F. Coughlin, and E. Feron, "Detection of driver fatigue caused by sleep deprivation," *IEEE Transactions on systems, man, and cybernetics-part A: Systems and humans*, vol. 39, no. 4, pp. 694–705, 2009.
[167] S. Furugori, N. Yoshizawa, C. Iname, and Y. Miura, "Estimation of driver fatigue by pressure distribution on seat in long term driving," *Review of automotive engineering*, vol. 26, no. 1, pp. 053–058, 2005.
[168] T. Wakita, K. Ozawa, C. Miyajima, K. Igarashi, K. Itou, K. Takeda, and F. Itakura, "Driver identification using driving behavior signals," *IEICE TRANSACTIONS on Information and Systems*, vol. 89, no. 3, pp. 1188–1194, 2006.
[169] L. M. Bergasa, J. Nuevo, M. A. Sotelo, R. Barea, and M. E. Lopez, "Real-time system for monitoring driver vigilance," *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 1, pp. 63–77, 2006.
[170] F. Friedrichs and B. Yang, "Camera-based drowsiness reference for driver state classification under real driving conditions," in *2010 IEEE Intelligent Vehicles Symposium*. IEEE, 2010, pp. 101–106.
[171] G. Borghini, G. Vecchiato, J. Toppi, L. Astolfi, A. Maglione, R. Isabella, C. Caltagirone, W. Kong, D. Wei, Z. Zhou *et al.*, "Assessment of mental fatigue during car driving by using high resolution eeg activity and neurophysiologic indices," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 2012, pp. 6442–6445.
[172] F.-C. Lin, L.-W. Ko, C.-H. Chuang, T.-P. Su, and C.-T. Lin, "Generalized eeg-based drowsiness prediction system by using a self-organizing neural fuzzy system," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 59, no. 9, pp. 2044–2055, 2012.
[173] G. Zhang and A. Etemad, "Capsule attention for multimodal eeg-eog representation learning with application to driver vigilance estimation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 1138–1149, 2021.
[174] F. Guede-Fernández, M. Fernández-Chimeno, J. Ramos-Castro, and M. A. García-González, "Driver drowsiness detection based on respiratory signal analysis," *IEEE Access*, vol. 7, pp. 81 826–81 838, 2019.
[175] T.-Y. Hu, X. Xie, and J. Li, "Negative or positive? the effect of emotion and mood on risky driving," *Transportation research part F: traffic psychology and behaviour*, vol. 16, pp. 29–40, 2013.
[176] J. P. DePasquale, E. S. Geller, S. W. Clarke, and L. C. Littleton, "Measuring road rage: Development of the propensity for angry driving scale," *Journal of Safety Research*, vol. 32, no. 1, pp. 1–16, 2001.
[177] B.-J. Park, C. Yoon, E.-H. Jang, and D.-H. Kim, "Physiological signals and recognition of negative emotions," in *2017 International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE, 2017, pp. 1074–1076.
[178] C. D. Monaco and S. N. Brennan, "Radarodo: Ego-motion estimation from doppler and spatial data in radar images," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 3, pp. 475–484, 2020.
[179] P. J. Bota, C. Wang, A. L. Fred, and H. P. Da Silva, "A review, current challenges, and future possibilities on emotion recognition using machine learning and physiological signals," *IEEE Access*, vol. 7, pp. 140 990–141 020, 2019.
[180] I. B. Mauss and M. D. Robinson, "Measures of emotion: A review," *Cognition and emotion*, vol. 23, no. 2, pp. 209–237, 2009.
[181] J. S. Lerner, Y. Li, P. Valdesolo, and K. S. Kassam, "Emotion and decision making," *Annual review of psychology*, vol. 66, pp. 799–823, 2015.
[182] P. Ekman, T. Dalgleish, and M. Power, "Handbook of cognition and emotion," *Chihester, UK: Wiley*, 1999.
[183] H. Gunes, B. Schuller, M. Pantic, and R. Cowie, "Emotion representation, analysis and synthesis in continuous space: A survey," in *2011 IEEE International Conference on Automatic Face Gesture Recognition (FG)*, 2011, pp. 827–834.
[184] A. G. Money and H. Agius, "Analysing user physiological responses for affective video summarisation," *Displays*, vol. 30, no. 2, pp. 59–70, 2009.
[185] K. W. Lee, H. S. Yoon, J. M. Song, and K. R. Park, "Convolutional neural network-based classification of driver's emotion during aggressive and smooth driving using multi-modal camera sensors," *Sensors*, vol. 18, no. 4, p. 957, 2018.
[186] R. W. Levenson, "The autonomic nervous system and emotion," *Emotion review*, vol. 6, no. 2, pp. 100–112, 2014.
[187] S. Katsigiannis and N. Ramzan, "Dreamer: A database for emotion recognition through eeg and ecg signals from wireless low-cost off-the-shelf devices," *IEEE journal of biomedical and health informatics*, vol. 22, no. 1, pp. 98–107, 2017.
[188] M. Soleymani, J. Lichtenauer, T. Pun, and M. Pantic, "A multimodal database for affect recognition and implicit tagging," *IEEE transactions on affective computing*, vol. 3, no. 1, pp. 42–55, 2011.
[189] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "Deap: A database for emotion analysis; using physiological signals," *IEEE transactions on affective computing*, vol. 3, no. 1, pp. 18–31, 2011.
[190] M. Elgendi, "On the analysis of fingertip photoplethysmogram signals," *Current cardiology reviews*, vol. 8, no. 1, pp. 14–25, 2012.
[191] G. Valenza, P. Allegrini, A. Lanatà, and E. P. Scilingo, "Dominant lyapunov exponent and approximate entropy in heart rate variability during emotional visual elicitation," *Frontiers in neuroengineering*, vol. 5, p. 3, 2012.
[192] D. S. Quintana, A. J. Guastella, T. Outhred, I. B. Hickie, and A. H. Kemp, "Heart rate variability is associated with emotion recognition: direct evidence for a relationship between the autonomic nervous system and social cognition," *International journal of psychophysiology*, vol. 86, no. 2, pp. 168–172, 2012.
[193] D. Jiang, K. Wu, D. Chen, G. Tu, T. Zhou, A. Garg, and L. Gao, "A probability and integrated learning based classification algorithm for high-level human emotion recognition problems," *Measurement*, vol. 150, p. 107049, 2020.
[194] M. Hu, H. Wang, X. Wang, J. Yang, and R. Wang, "Video facial emotion recognition based on local enhanced motion history image and cnn-ctslstm networks," *Journal of Visual Communication and Image Representation*, vol. 59, pp. 176–185, 2019.
[195] S. Wu, Z. Du, W. Li, D. Huang, and Y. Wang, "Continuous emotion recognition in videos by fusing facial expression, head pose and eye gaze," in *2019 International Conference on Multimodal Interaction*, 2019, pp. 40–48.
[196] S. Mariooryad and C. Busso, "Facial expression recognition in the presence of speech using blind lexical compensation," *IEEE Transactions on Affective Computing*, vol. 7, no. 4, pp. 346–359, 2015.
[197] F. Xu, J. Zhang, and J. Z. Wang, "Microexpression identification and categorization using a facial dynamics map," *IEEE Transactions on Affective Computing*, vol. 8, no. 2, pp. 254–267, 2017.
[198] G. Du, Z. Wang, B. Gao, S. Mumtaz, K. M. Abualnaja, and C. Du, "A convolution bidirectional long short-term memory neural network for driver emotion recognition," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 7, pp. 4570–4578, 2021.
[199] H. Monkaresi, N. Bosch, R. A. Calvo, and S. K. D'Mello, "Automated detection of engagement using video-based estimation of facial expressions and heart rate," *IEEE Transactions on Affective Computing*, vol. 8, no. 1, pp. 15–28, 2016.
[200] J.-M. López-Gil, J. Virgili-Gomá, R. Gil, T. Guilera, I. Batalla, J. Soler-González, and R. García, "Method for improving eeg based emotion recognition by combining it with synchronized biometric and eye

tracking technologies in a non-invasive and low cost way," *Frontiers in computational neuroscience*, vol. 10, p. 85, 2016.

[201] S. Ramakrishnan and I. M. El Emary, "Speech emotion recognition approaches in human computer interaction," *Telecommunication Systems*, vol. 52, no. 3, pp. 1467–1478, 2013.

[202] Y. Pan, P. Shen, and L. Shen, "Speech emotion recognition using support vector machine," *International Journal of Smart Home*, vol. 6, no. 2, pp. 101–108, 2012.

[203] J. Wu, Z. Huang, and C. Lv, "Uncertainty-aware model-based reinforcement learning: Methodology and application in autonomous driving," *IEEE Transactions on Intelligent Vehicles*, 2022.

[204] J. D. Lee and K. A. See, "Trust in automation: Designing for appropriate reliance," *Human factors*, vol. 46, no. 1, pp. 50–80, 2004.

[205] R. Parasuraman and V. Riley, "Humans and automation: Use, misuse, disuse, abuse," *Human factors*, vol. 39, no. 2, pp. 230–253, 1997.

[206] K. A. Hoff and M. Bashir, "Trust in automation: Integrating empirical evidence on factors that influence trust," *Human factors*, vol. 57, no. 3, pp. 407–434, 2015.

[207] M. Körber, E. Baseler, and K. Bengler, "Introduction matters: Manipulating trust in automation and reliance in automated driving," *Applied ergonomics*, vol. 66, pp. 18–31, 2018.

[208] J. C. Christensen and J. B. Lyons, "Trust between humans and learning machines: developing the gray box," *Mechanical Engineering*, vol. 139, no. 06, pp. S9–S13, 2017.

[209] P. Jing, G. Xu, Y. Chen, Y. Shi, and F. Zhan, "The determinants behind the acceptance of autonomous vehicles: A systematic review," *Sustainability*, vol. 12, no. 5, p. 1719, 2020.

[210] K. F. Yuen, Y. D. Wong, F. Ma, and X. Wang, "The determinants of public acceptance of autonomous vehicles: An innovation diffusion perspective," *Journal of Cleaner Production*, vol. 270, p. 121904, 2020.

[211] C. Olaverri-Monreal, "Promoting trust in self-driving vehicles," *Nature Electronics*, vol. 3, no. 6, pp. 292–294, 2020.

[212] J. K. Choi and Y. G. Ji, "Investigating the importance of trust on adopting an autonomous vehicle," *International Journal of Human-Computer Interaction*, vol. 31, no. 10, pp. 692–702, 2015.

[213] M. Dikmen and C. Burns, "Trust in autonomous vehicles: The case of tesla autopilot and summon," in *2017 IEEE International conference on systems, man, and cybernetics (SMC)*. IEEE, 2017, pp. 1093–1098.

[214] K. E. Schaefer and D. R. Scribner, "Individual differences, trust, and vehicle autonomy: A pilot study," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, no. 1. SAGE Publications Sage CA: Los Angeles, CA, 2015, pp. 786–790.

[215] T. Zhang, D. Tao, X. Qu, X. Zhang, J. Zeng, H. Zhu, and H. Zhu, "Automated vehicle acceptance in china: Social influence and initial trust are key determinants," *Transportation research part C: emerging technologies*, vol. 112, pp. 220–233, 2020.

[216] A. Z. Benleulmi and T. Blecker, "Investigating the factors influencing the acceptance of fully autonomous cars," in *Digitalization in Supply Chain Management and Logistics: Smart and Digital Solutions for an Industry 4.0 Environment. Proceedings of the Hamburg International Conference of Logistics (HICL), Vol. 23*. Berlin: epubli GmbH, 2017, pp. 99–115.

[217] P. Bansal, K. M. Kockelman, and A. Singh, "Assessing public opinions of and interest in new vehicle technologies: An austin perspective," *Transportation Research Part C: Emerging Technologies*, vol. 67, pp. 1–14, 2016.

[218] W. Li, N. Yao, Y. Shi, W. Nie, Y. Zhang, X. Li, J. Liang, F. Chen, and Z. Gao, "Personality openness predicts driver trust in automated driving," *Automotive Innovation*, vol. 3, no. 1, pp. 3–13, 2020.

[219] J.-Y. Jian, A. M. Bisantz, and C. G. Drury, "Foundations for an empirically determined scale of trust in automated systems," *International journal of cognitive ergonomics*, vol. 4, no. 1, pp. 53–71, 2000.

[220] S. Khastgir, S. Birrell, G. Dhadyalla, and P. Jennings, "Calibrating trust through knowledge: Introducing the concept of informed safety for automation in vehicles," *Transportation research part C: emerging technologies*, vol. 96, pp. 290–303, 2018.

[221] J. Haspiel, N. Du, J. Meyerson, L. P. Robert Jr, D. Tilbury, X. J. Yang, and A. K. Pradhan, "Explanations and expectations: Trust building in automated vehicles," in *Companion of the 2018 ACM/IEEE international conference on human-robot interaction*, 2018, pp. 119–120.

[222] M. F. Jung, D. Sirkin, T. M. Gür, and M. Steinert, "Displayed uncertainty improves driving experience and behavior: The case of range anxiety in an electric car," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 2015, pp. 2201–2210.

[223] K. Okamura and S. Yamada, "Adaptive trust calibration for supervised autonomous vehicles," in *Adjunct proceedings of the 10th international conference on automotive user interfaces and interactive vehicular applications*, 2018, pp. 92–97.

[224] W. Payre, J. Cestac, and P. Delhomme, "Fully automated driving: Impact of trust and practice on manual control recovery," *Human factors*, vol. 58, no. 2, pp. 229–241, 2016.

[225] S. Hergeth, L. Lorenz, R. Vilimek, and J. F. Krems, "Keep your scanners peeled: Gaze behavior as a measure of automation trust during highly automated driving," *Human factors*, vol. 58, no. 3, pp. 509–519, 2016.

[226] W. Wang, W. Han, X. Na, J. Gong, and J. Xi, "A probabilistic approach to measuring driving behavior similarity with driving primitives," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 1, pp. 127–138, 2020.

[227] S. Scherer, A. Dettmann, F. Hartwich, T. Pech, A. C. Bullinger, and G. Wanielik, "How the driver wants to be driven-modelling driving styles in highly automated driving," in *7. Tagung Fahrerassistenzsysteme*, 2015.

[228] F. Hartwich, M. Beggiato, A. Dettmann, and J. F. Krems, "Drive me comfortable: Customized automated driving styles for younger and older drivers. 8," *VDI-Tagung "Der Fahrer im*, vol. 21, pp. 442–456, 2015.

[229] N. M. Yusof, J. Karjanto, J. Terken, F. Delbressine, M. Z. Hassan, and M. Rauterberg, "The exploration of autonomous vehicle driving styles: preferred longitudinal, lateral, and vertical accelerations," in *Proceedings of the 8th international conference on automotive user interfaces and interactive vehicular applications*, 2016, pp. 245–252.

[230] C. Basu, Q. Yang, D. Hungerman, M. Sinahal, and A. D. Draqan, "Do you want your autonomous car to drive like you?" in *2017 12th ACM/IEEE International Conference on Human-Robot Interaction (HRI*. IEEE, 2017, pp. 417–425.

[231] M. Kuderer, S. Gulati, and W. Burgard, "Learning driving styles for autonomous vehicles from demonstration," in *2015 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2015, pp. 2641–2646.

[232] P. Hang, C. Lv, Y. Xing, C. Huang, and Z. Hu, "Human-like decision making for autonomous driving: A noncooperative game theoretic approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 4, pp. 2076–2087, 2020.

[233] Y. Lu and L. Bi, "Human behavior model-based predictive control of longitudinal brain-controlled driving," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 3, pp. 1361–1374, 2021.

[234] J.-L. Yin, B.-H. Chen, and K.-H. R. Lai, "Driver danger-level monitoring system using multi-sourced big driving data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 12, pp. 5271–5282, 2020.

[235] L. Pozueco, N. Gupta, X. G. Pañeda, R. García, A. G. Tuero, D. Melendi, A. Rionda, and V. Corcoba, "Analysis of driving patterns and on-board feedback-based training for proactive road safety monitoring," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 6, pp. 529–537, 2020.

[236] X. Wang, Y. Guo, C. Bai, Q. Yuan, S. Liu, and J. Han, "Driver's intention identification with the involvement of emotional factors in two-lane roads," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 11, pp. 6866–6874, 2021.

[237] N. Khairdoost, M. Shirpour, M. A. Bauer, and S. S. Beauchemin, "Real-time driver maneuver prediction using lstm," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 4, pp. 714–724, 2020.

[238] Z. Wang, X. Liao, C. Wang, D. Oswald, G. Wu, K. Boriboonsomsin, M. J. Barth, K. Han, B. Kim, and P. Tiwari, "Driver behavior modeling using game engine and real vehicle: A learning-based approach," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 4, pp. 738–749, 2020.

[239] A. P. Bolduc, L. Guo, and Y. Jia, "Multimodel approach to personalized autonomous adaptive cruise control," *IEEE Transactions on Intelligent Vehicles*, vol. 4, no. 2, pp. 321–330, 2019.

[240] J. Huang, Y. Chen, X. Peng, L. Hu, and D. Cao, "Study on the driving style adaptive vehicle longitudinal control strategy," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 4, pp. 1107–1115, 2020.

[241] C. Wei, E. Paschalidis, N. Merat, A. Solernou, F. Hajiseyedjavadi, and R. Romano, "Human-like decision making and motion control for smooth and natural car following," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2021.

[242] A. Rosenfeld, Z. Bareket, C. V. Goldman, D. J. LeBlanc, and O. Tsimhoni, "Learning drivers' behavior to improve adaptive cruise control," *Journal of Intelligent Transportation Systems*, vol. 19, no. 1, pp. 18–31, 2015.

[243] M. Canale, S. Malan, and V. Murdocco, "Personalization of acc stop and go task based on human driver behaviour analysis," *IFAC*

Proceedings Volumes, vol. 35, no. 1, pp. 357–362, 2002.

[244] S. Lefèvre, A. Carvalho, Y. Gao, H. E. Tseng, and F. Borrelli, "Driver models for personalised driving assistance," *Vehicle System Dynamics*, vol. 53, no. 12, pp. 1705–1720, 2015.

[245] G. N. Bifulco, L. Pariota, F. Simonelli, and R. Di Pace, "Development and testing of a fully adaptive cruise control system," *Transportation Research Part C: Emerging Technologies*, vol. 29, pp. 156–170, 2013.

[246] S. Lefèvre, A. Carvalho, and F. Borrelli, "A learning-based framework for velocity control in autonomous driving," *IEEE Transactions on Automation Science and Engineering*, vol. 13, no. 1, pp. 32–42, 2016.

[247] S. Ramyar, A. Homaifar, S. M. Salaken, S. Nahavandi, and A. Kurt, "A personalized highway driving assistance system," in *2017 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2017, pp. 1596–1601.

[248] X. Chen, Y. Zhai, C. Lu, J. Gong, and G. Wang, "A learning model for personalized adaptive cruise control," in *2017 IEEE intelligent vehicles symposium (IV)*. IEEE, 2017, pp. 379–384.

[249] J. Wang, L. Zhang, D. Zhang, and K. Li, "An adaptive longitudinal driving assistance system based on driver characteristics," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 1, pp. 1–12, 2012.

[250] G. N. Bifulco, F. Simonelli, and R. Di Pace, "Experiments toward an human-like adaptive cruise control," in *2008 IEEE intelligent vehicles symposium*. IEEE, 2008, pp. 919–924.

[251] J. Wang, L. Zhang, D. Zhang, and K. Li, "An adaptive longitudinal driving assistance system based on driver characteristics," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 1, pp. 1–12, 2013.

[252] J. Wang, C. Yu, S. E. Li, and L. Wang, "A forward collision warning algorithm with adaptation to driver behaviors," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 4, pp. 1157–1167, 2016.

[253] F. Muehlfeld, I. Doric, R. Ertlmeier, and T. Brandmeier, "Statistical behavior modeling for driver-adaptive precrash systems," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 4, pp. 1764–1772, 2013.

[254] V. Govindarajan, K. Driggs-Campbell, and R. Bajcsy, "Affective driver state monitoring for personalized, adaptive adas," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 1017–1022.

[255] W. Wang, D. Zhao, W. Han, and J. Xi, "A learning-based approach for lane departure warning systems with a personalized driver model," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 10, pp. 9145–9157, 2018.

[256] W. Wang, J. Xi, C. Liu, and X. Li, "Human-centered feed-forward control of a vehicle steering system based on a driver's path-following characteristics," *IEEE transactions on intelligent transportation systems*, vol. 18, no. 6, pp. 1440–1453, 2016.

[257] S. Schnelle, J. Wang, H.-J. Su, and R. Jagacinski, "A personalizable driver steering model capable of predicting driver behaviors in vehicle collision avoidance maneuvers," *IEEE Transactions on Human-Machine Systems*, vol. 47, no. 5, pp. 625–635, 2016.

[258] S. Schnelle, J. Wang, H. Su, and R. Jagacinski, "A driver steering model with personalized desired path generation," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 1, pp. 111–120, 2016.

[259] V. A. Butakov and P. Ioannou, "Personalized driver/vehicle lane change models for adas," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 10, pp. 4422–4431, 2014.

[260] C. Vallon, Z. Ercan, A. Carvalho, and F. Borrelli, "A machine learning approach for personalized autonomous lane change initiation and control," in *2017 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2017, pp. 1590–1595.

[261] Y. Lu, J. Liang, G. Yin, L. Xu, J. Wu, J. Feng, and F. Wang, "A shared control design for steering assistance system considering driver behaviors," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2022.

[262] S. Ansari, F. Naghdy, and H. Du, "Human-machine shared driving: Challenges and future directions," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2022.

[263] W. Wang, X. Na, D. Cao, J. Gong, J. Xi, Y. Xing, and F.-Y. Wang, "Decision-making in driver-automation shared control: A review and perspectives," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 5, pp. 1289–1307, 2020.

[264] C. Lv, Y. Li, Y. Xing, C. Huang, D. Cao, Y. Zhao, and Y. Liu, "Human–machine collaboration for automated driving using an intelligent two-phase haptic interface," *Advanced Intelligent Systems*, vol. 3, no. 4, p. 2000229, 2021.

[265] J. Terken and B. Pfleging, "Toward shared control between automated vehicles and users," *Automotive Innovation*, vol. 3, no. 1, pp. 53–61, 2020.

[266] K. Yuen and M. M. Trivedi, "Looking at hands in autonomous vehicles: A convnet approach using part affinity fields," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 3, pp. 361–371, 2020.

[267] J. Liu, Q. Dai, H. Guo, J. Guo, and H. Chen, "Human-oriented online driving authority optimization for driver-automation shared steering control," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2022.

[268] J. Tan, C. Xu, L. Li, F.-Y. Wang, D. Cao, and L. Li, "Guidance control for parallel parking tasks," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 1, pp. 301–306, 2020.

[269] X. Na and D. Cole, "Theoretical and experimental investigation of driver noncooperative-game steering control behavior," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 1, pp. 189–205, 2021.

[270] N. Deo and M. M. Trivedi, "Looking at the driver/rider in autonomous vehicles to predict take-over readiness," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 1, pp. 41–52, 2020.

[271] M.-P. Pacaux-Lemoine, P. Simon, and J.-C. Popieul, "Human-machine cooperation principles to support driving automation systems design," *FAST zero*, 2015.

[272] D. Orth, D. Kolossa, M. S. Paja, K. Schaller, A. Pech, and M. Heckmann, "A maximum likelihood method for driver-specific critical-gap estimation," in *2017 ieee intelligent vehicles symposium (iv)*. IEEE, 2017, pp. 553–558.

[273] C. Huang, P. Hang, Z. Hu, and C. Lv, "Collision-probability-aware human-machine cooperative planning for safe automated driving," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 10, pp. 9752–9763, 2021.

[274] C. Huang, H. Huang, J. Zhang, P. Hang, Z. Hu, and C. Lv, "Human-machine cooperative trajectory planning and tracking for safe automated driving," *IEEE Transactions on Intelligent Transportation Systems*, 2021.

[275] C. Huang, C. Lv, P. Hang, Z. Hu, and Y. Xing, "Human machine adaptive shared control for safe driving under automation degradation," *IEEE Intelligent Transportation Systems Magazine*, 2021.

[276] M. Li, H. Cao, X. Song, Y. Huang, J. Wang, and Z. Huang, "Shared control driver assistance system based on driving intention and situation assessment," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 11, pp. 4982–4994, 2018.

[277] P. Hang, X. Chen, and W. Wang, "Cooperative control framework for human driver and active rear steering system to advance active safety," *IEEE Transactions on Intelligent Vehicles*, vol. 6, no. 3, pp. 460–469, 2021.

[278] C. Olaverri-Monreal and T. Jizba, "Human factors in the design of human–machine interaction: An overview emphasizing v2x communication," *IEEE Transactions on Intelligent Vehicles*, vol. 1, no. 4, pp. 302–313, 2016.

[279] Z. Hu, Y. Hu, J. Liu, B. Wu, D. Han, and T. Kurfess, "3d separable convolutional neural network for dynamic hand gesture recognition," *Neurocomputing*, vol. 318, pp. 151–161, 2018.

[280] Hu, Zhongxu and Hu, Youmin and Liu, Jie and Wu, Bo and Han, Dongmin and Kurfess, Thomas, "A crnn module for hand pose estimation," *Neurocomputing*, vol. 333, pp. 157–168, 2019.

[281] Z. Hu, Y. Hu, B. Wu, J. Liu, D. Han, and T. Kurfess, "Hand pose estimation with multi-scale network," *Applied Intelligence*, vol. 48, no. 8, pp. 2501–2515, 2018.

[282] Z. Tan, N. Dai, Y. Su, R. Zhang, Y. Li, D. Wu, and S. Li, "Human-machine interaction in intelligent and connected vehicles: A review of status quo, issues and opportunities," *IEEE Transactions on Intelligent Transportation Systems*, 2021.

[283] Y. Lu and L. Bi, "Eeg signals-based longitudinal control system for a brain-controlled vehicle," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 2, pp. 323–332, 2018.

[284] A. Benloucif, A.-T. Nguyen, C. Sentouh, and J.-C. Popieul, "Cooperative trajectory planning for haptic shared control between driver and automation in highway driving," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 12, pp. 9846–9857, 2019.

[285] L. Li, W.-L. Huang, Y. Liu, N.-N. Zheng, and F.-Y. Wang, "Intelligence testing for autonomous vehicles: A new approach," *IEEE Transactions on Intelligent Vehicles*, vol. 1, no. 2, pp. 158–166, 2016.

[286] S. M. Thornton, B. Limonchik, F. E. Lewis, M. J. Kochenderfer, and J. C. Gerdes, "Toward closing the loop on human values," *IEEE Transactions on Intelligent Vehicles*, vol. 4, no. 3, pp. 437–446, 2019.

[287] C. K. Allison and N. A. Stanton, "Constraining design: applying the insights of cognitive work analysis to the design of novel in-car interfaces to support eco-driving," *Automotive Innovation*, vol. 3, no. 1, pp. 30–41, 2020.

[288] L. Li, Y. Liu, J. Wang, W. Deng, and H. Oh, "Human dynamics based

driver model for autonomous car," *IET Intelligent Transport Systems*, vol. 10, no. 8, pp. 545–554, 2016.

[289] M. Zhu, X. Wang, and Y. Wang, "Human-like autonomous car-following model with deep reinforcement learning," *Transportation research part C: emerging technologies*, vol. 97, pp. 348–368, 2018.

[290] W. Schwarting, A. Pierson, J. Alonso-Mora, S. Karaman, and D. Rus, "Social behavior for autonomous vehicles," *Proceedings of the National Academy of Sciences*, vol. 116, no. 50, pp. 24 972–24 978, 2019.

[291] S. Han, X. Wang, J. J. Zhang, D. Cao, and F.-Y. Wang, "Parallel vehicular networks: a cpss-based approach via multimodal big data in iov," *IEEE Internet of Things Journal*, vol. 6, no. 1, pp. 1079–1089, 2018.

[292] X. Wang, S. Han, L. Yang, T. Yao, and L. Li, "Parallel internet of vehicles: Acp-based system architecture and behavioral modeling," *IEEE Internet of Things Journal*, vol. 7, no. 5, pp. 3735–3746, 2020.

[293] A. O. Ly and M. Akhloufi, "Learning to drive by imitation: An overview of deep behavior cloning methods," *IEEE Transactions on Intelligent Vehicles*, vol. 6, no. 2, pp. 195–209, 2021.

[294] A. Papadoulis, M. Quddus, and M. Imprialou, "Evaluating the safety impact of connected and autonomous vehicles on motorways," *Accident Analysis & Prevention*, vol. 124, pp. 12–22, 2019.

[295] R. P. Bhattacharyya, D. J. Phillips, B. Wulfe, J. Morton, A. Kuefler, and M. J. Kochenderfer, "Multi-agent imitation learning for driving simulation," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2018, pp. 1534–1539.

[296] A. Amini, I. Gilitschenski, J. Phillips, J. Moseyko, R. Banerjee, S. Karaman, and D. Rus, "Learning robust control policies for end-to-end autonomous driving from data-driven simulation," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 1143–1150, 2020.

[297] S. Minaeian, Y. Yuan, J. Liu, and Y.-J. Son, "Human-in-the-loop agent-based simulation for improved autonomous surveillance using unmanned vehicles," in *2015 Winter Simulation Conference (WSC)*, 2015, pp. 3126–3127.

[298] X. Li, Y. Wang, L. Yan, K. Wang, F. Deng, and F.-Y. Wang, "Paralleleye-cs: A new dataset of synthetic images for testing the visual intelligence of intelligent vehicles," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 10, pp. 9619–9631, 2019.

[299] Y. Tian, X. Wang, Y. Shen, Z. Guo, Z. Wang, and F.-Y. Wang, "Parallel point clouds: Hybrid point cloud generation and 3d model enhancement via virtual–real integration," *Remote Sensing*, vol. 13, no. 15, p. 2868, 2021.

[300] Y. Yang, Y. Zhuang, and Y. Pan, "Multiple knowledge representation for big data artificial intelligence: framework, applications, and case studies," *Frontiers of Information Technology & Electronic Engineering*, vol. 22, no. 12, pp. 1551–1558, 2021.

[301] J. Duan, C. Hu, X. Zhan, H. Zhou, G. Liao, and T. Shi, "Ms-sspcanet: A powerful deep learning framework for tool wear prediction," *Robotics and Computer-Integrated Manufacturing*, vol. 78, p. 102391, 2022.

[302] J. Liu, C. Zhang, and X. Jiang, "Imbalanced fault diagnosis of rolling bearing using improved msr-gan and feature enhancement-driven capsnet," *Mechanical Systems and Signal Processing*, vol. 168, p. 108664, 2022.

[303] C. Yang, J. Liu, K. Zhou, M.-F. Ge, and X. Jiang, "Transferable graph features-driven cross-domain rotating machinery fault diagnosis," *Knowledge-Based Systems*, p. 109069, 2022.

[304] C. Yang, K. Zhou, and J. Liu, "Supergraph: Spatial-temporal graph-based feature extraction for rotating machinery diagnosis," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 4, pp. 4167–4176, 2021.

[305] J. Banzi, I. Bulugu, and Z. Ye, "Learning a deep predictive coding network for a semi-supervised 3d-hand pose estimation," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 5, pp. 1371–1379, 2020.

[306] K. Liu, Z. Ye, H. Guo, D. Cao, L. Chen, and F.-Y. Wang, "Fiss gan: A generative adversarial network for foggy image semantic segmentation," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 8, pp. 1428–1439, 2021.

[307] U. Michieli, M. Biasetton, G. Agresti, and P. Zanuttigh, "Adversarial learning and self-teaching techniques for domain adaptation in semantic segmentation," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 3, pp. 508–518, 2020.

[308] S. Harford, F. Karim, and H. Darabi, "Generating adversarial samples on multivariate time series using variational autoencoders," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 9, pp. 1523–1538, 2021.

[309] S. Pu, W. Zhao, W. Chen, S. Yang, D. Xie, and Y. Pan, "Unsupervised object detection with scene-adaptive concept learning," *Frontiers of Information Technology & Electronic Engineering*, vol. 22, no. 5, pp. 638–651, 2021.

[310] W. Wang, A. Ramesh, J. Zhu, J. Li, and D. Zhao, "Clustering of driving encounter scenarios using connected vehicle trajectories," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 3, pp. 485–496, 2020.

[311] L. Hou, X.-y. Luo, Z.-y. Wang, and J. Liang, "Representation learning via a semi-supervised stacked distance autoencoder for image classification," *Frontiers of Information Technology & Electronic Engineering*, vol. 21, no. 7, pp. 1005–1018, 2020.

[312] C. Wang, W. Pedrycz, Z. Li, and M. Zhou, "Residual-driven fuzzy c-means clustering for image segmentation," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 4, pp. 876–889, 2021.

[313] L.-y. Xue, Q.-r. Mao, X.-h. Huang, and J. Chen, "Nlwsnet: a weakly supervised network for visual sentiment analysis in mislabeled web images," *Frontiers of Information Technology & Electronic Engineering*, vol. 21, no. 9, pp. 1321–1333, 2020.

[314] J.-w. Hu, B.-y. Zheng, C. Wang, C.-h. Zhao, X.-l. Hou, Q. Pan, and Z. Xu, "A survey on multi-sensor fusion based obstacle detection for intelligent ground vehicles in off-road environments," *Frontiers of Information Technology & Electronic Engineering*, vol. 21, no. 5, pp. 675–692, 2020.

[315] C. Sun, J. M. U. Vianney, Y. Li, L. Chen, L. Li, F.-Y. Wang, A. Khajepour, and D. Cao, "Proximity based automatic data annotation for autonomous driving," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 2, pp. 395–404, 2020.

[316] Y. Liu, Z. Wang, K. Han, Z. Shou, P. Tiwari, and J. Hansen, "Vision-cloud data fusion for adas: A lane change prediction case study," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2021.

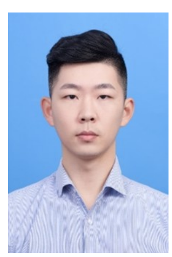
[317] T. Zhou, M. Chen, and J. Zou, "Reinforcement learning based data fusion method for multi-sensors," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 6, pp. 1489–1497, 2020.

[318] M. Ghahramani, M. Zhou, and G. Wang, "Urban sensing based on mobile phone data: approaches, applications, and challenges," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 3, pp. 627–637, 2020.

[319] J. Nie, J. Yan, H. Yin, L. Ren, and Q. Meng, "A multimodality fusion deep neural network and safety test strategy for intelligent vehicles," *IEEE Transactions on Intelligent Vehicles*, vol. 6, no. 2, pp. 310–322, 2021.

[320] C. Xu, H. Wu, H. Liu, W. Gu, Y. Li, and D. Cao, "Blockchain-oriented privacy protection of sensitive data in the internet of vehicles," *IEEE Transactions on Intelligent Vehicles*, pp. 1–1, 2022.

[321] M. Hasan, S. Mohan, T. Shimizu, and H. Lu, "Securing vehicle-to-everything (v2x) communication platforms," *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 4, pp. 693–713, 2020.



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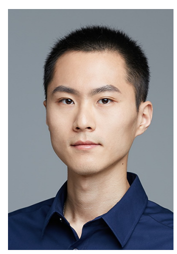

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