



The Security of Autonomous Driving: Threats, Defenses, and Future Directions

By KUI REN¹, Fellow IEEE, QIAN WANG², Senior Member IEEE, CONG WANG³, Senior Member IEEE, ZHAN QIN, Member IEEE, AND XIAODONG LIN⁴, Fellow IEEE

ABSTRACT | Autonomous vehicles (AVs) have promised to drastically improve the convenience of driving by releasing the burden of drivers and reducing traffic accidents with more precise control. With the fast development of artificial intelligence and significant advancements of the Internet of Things technologies, we have witnessed the steady progress of autonomous driving over the recent years. As promising as it is, the march of autonomous driving technologies also faces new challenges, among which security is the top concern. In this article, we give a systematic study on the security threats surrounding autonomous driving, from the angles of perception, navigation, and control. In addition to the in-depth overview of

these threats, we also summarize the corresponding defense strategies. Furthermore, we discuss future research directions about the new security threats, especially those related to deep-learning-based self-driving vehicles. By providing the security guidelines at this early stage, we aim to promote new techniques and designs related to AVs from both academia and industry and boost the development of secure autonomous driving.

KEYWORDS | Autonomous vehicles (AVs); in-vehicle protocol; in-vehicle systems; security; sensors.

I. INTRODUCTION

Since the CMU Navlab Group built the first computer-controlled vehicles for automated driving in 1984 [1], many researchers have promoted autonomous vehicle (AV) developments. One noteworthy breakthrough was in 1994, when the Group of UniBw Munich and the Group of Daimler-Benz have codeveloped an AV that could reach the speed up to 130 km/h [2]. That very AV could automatically track different lane markings and decide when to change between lanes.

Recently, with the prevalence of artificial intelligence (AI) and Internet of Things (IoT) technologies, autonomous driving has gained steady improvements and is getting more and more intelligent to precisely sense environments in the real world, quickly analyze the sensor data, and autonomously make complex decisions. In the foreseeable future, AVs are widely believed to be one of the most popular AI applications in people's daily lives. For instance, IHS Markit predicts that the annual sales of AVs will exceed 33 million in 2040 [3].

Manuscript received June 10, 2019; revised September 20, 2019; accepted October 10, 2019. The work of K. Ren was supported in part by the NSFC under Grant 61772236 and in part by the Zhejiang Key R&D Plan under Grant 2019C03133. The work of Q. Wang was supported in part by the NSFC under Grant 61822207 and Grant U1636219, in part by the Equipment Pre-Research Joint Fund of Ministry of Education of China (Youth Talent) under Grant 6141A02033327, in part by the Outstanding Youth Foundation of Hubei Province under Grant 2017CFA047, and in part by the Fundamental Research Funds for the Central Universities under Grant 2042019kf0210. The work of C. Wang was supported in part by the Research Grants Council of Hong Kong under Grant CityU C1008-16G and in part by the NSFC under Grant 61572412. The work of Z. Qin was supported in part by Major Scientific Research Project of Zhejiang Lab under Grant 2018FD0ZX01. (Corresponding author: Kui Ren.)

K. Ren and **Z. Qin** are with the Institute of Cyberspace Research, Zhejiang University, Hangzhou 310027, China, with the College of Computer Science and Technology, Zhejiang University, Hangzhou 310027, China, and also with the Alibaba-Zhejiang University Joint Institute of Frontier Technologies, Zhejiang University, Hangzhou 310027, China (e-mail: kuiren@zju.edu.cn; qinzhao@zju.edu.cn).

Q. Wang is with the School of Cyber Science and Engineering, Wuhan University, Wuhan 430072, China (e-mail: qianwang@whu.edu.cn).

C. Wang is with the Department of Computer Science, City University of Hong Kong, Hong Kong (e-mail: congwang@cityu.edu.hk).

X. Lin is with the School of Computer Science, University of Guelph, Guelph, ON N1G 2W1, Canada (e-mail: xlin08@uoguelph.ca).

Digital Object Identifier 10.1109/JPROC.2019.2948775

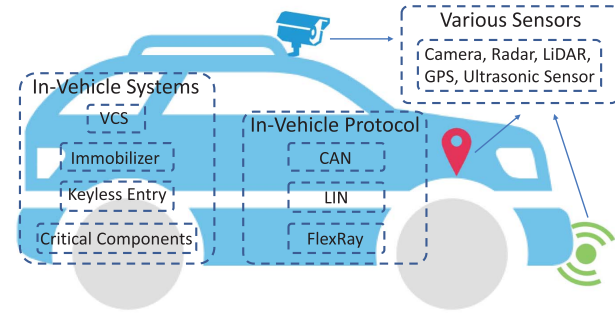


Fig. 1. Three types of attack surfaces of an AV.

As promising as it is, the fast development of autonomous driving technologies also faces new challenges, among which security is the top concern. Specifically, before the wide adoption of AVs on the road facing realistic traffic conditions, the security and trustworthiness of AVs must be guaranteed through all kinds of technical assurances. As we know, AVs are often equipped with varieties of functionally rich sensors, such as cameras, radars, and GPS, to perceive its surrounding environments. The data captured by sensors are fed into the AV's computing system for rounds of complicated processing and calculations in order to enable the autonomous control of the vehicle, including the braking mechanism and the engine. Hence, AVs heavily rely on the sensor data to make the right driving decisions, which inevitably enlarges the potential threat surface and incurs serious security risks from sensors [4]. In addition, the systems responsible for in-vehicle access and control [e.g., voice controllable systems (VCSs) and keyless entry systems], and the protocols indispensable for in-vehicle network operations [e.g., controller area networks (CANs)] also require effective security countermeasures against various attacks while providing critical and decisive functionalities for AVs.

In Fig. 1, we briefly categorize the broadly defined security threats surrounding an AV into three classes. The first type contains different kinds of sensors equipped in the vehicle, which perceive the surrounding road conditions. The sensor data are further used to guide driving without human intervention. Once they are jammed or spoofed by false signals, the autonomous driving car will lose the ability of precisely sensing the environments. The second one includes various in-vehicle access and control systems, e.g., the vehicle immobilizer, the keyless entry system, the critical control components, and the VCS. These in-vehicle systems guarantee the security of physical car access and human-vehicle interaction. If these in-vehicle access and control systems are broken, it would lead to critical security flaws and incidents to AV, as serious as a matter of life and death. The last is about the in-vehicle network protocols, such as the local interconnect network (LIN), the CAN mentioned earlier, and FlexRay. Any vulnerability of the protocols could be exploited through telematics

modules and further magnified remotely by the attackers to illegally control the vehicles.

In this article, we first give a systematic study on the categories of security threats, particularly from the perspectives of perception, navigation, and control. We then, respectively, summarize the corresponding defense strategies. Last but not least, we highlight a few crucial open problems, especially those related to deep-learning-based self-driving vehicles, and discuss future research directions. We believe that our work can encourage new techniques and designs related to defenses against threats posed to AVs and push forward the frontier and future development of secure autonomous driving.

II. POTENTIAL THREATS OF SENSORS

When AVs cruise on the road, it is essential for AVs to sense the environmental circumstances precisely due to the lack of drivers' control. Various sensors, such as GPS, ultrasonic sensor, light detection and ranging (LiDAR), and millimeter-wave (MMW) radar, are "eyes" indispensable for AVs. Fig. 2 illustrates sensors embedded in AVs, and Table 1 shows a generic description of these sensors as well as the corresponding usage scenarios for them. Armed with sensors, AVs can achieve environment perception, collision avoidance, obstacle/pedestrian recognition, navigation, and so on. Considering such high reliance on sensors, once sensors are blinded, or even maliciously controlled, it may cause lethal catastrophes.

In this section, we introduce various types of attacks against most common sensors in AVs and provide some corresponding defense strategies.

A. Various Types of Attacks

1) *Attacks Against GPS*: GPS is indispensable in the navigation of AVs. Relying on position got from GPS and aided by a precise map, AVs can choose an optimized, shortest path from one location to another location, even without any previous knowledge. This is essential for AVs to work correctly without the assistance of drivers. Meanwhile, this also exposes vulnerabilities to malicious attackers.

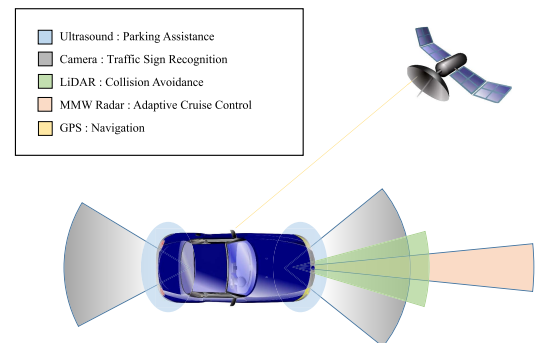


Fig. 2. Sensors embed in AV.

Table 1 Various Types of Sensors

| Sensors | Signal | Working Area | Principle | Usage |
|-------------------|----------------|--------------|-----------|--|
| GPS | Microwave | Global | Passive | Navigation |
| LiDAR | Infrared laser | Medium range | Active | Pedestrian detection Collision avoidance |
| MMW Radar | Microwave | Long range | Active | Collision avoidance Adaptive cruise control |
| Ultrasonic Sensor | Ultrasound | Proximity | Active | Parking assistance |
| Camera | Visible light | Short range | Passive | Traffic sign recognition Lane detection Obstacle detection |

The attacks toward GPS have been studied widely in the past decade [5]–[11]. Existing attacks, such as in [6], [9], [12], and [13], demonstrate that the GPS attacks are practical. There are mainly two kinds of GPS attacks: spoofing and jamming. GPS signals from satellites are weak due to long-distance traveling [6]. Hence, the jamming attack is much easy to be launched by using stronger signals in the same frequencies. In the following part, we focus on introducing spoofing attacks since they are more threatening than jamming.

Spoofing aims to drag victims off to incorrect position (and time) by fabricating spurious signals that deviate the correct position of victims. A simple strategy that could be easily detected is to first jam the victim's GPS receiver and make it lose the lock of the signals. Then, the attacker sends a much powerful spurious signal to take over the signals from satellites [6]. This attack is detectable since the victim's GPS loses signals or encounters an abrupt change [7]. A much more sophisticated strategy needs the attacker to be more patient [7], [10], [11]. To mount an attack toward the victim, the spurious signals of the attacker should synchronize on the signals from the satellite. After synchronization, the attacker increases the power of spurious signals, which makes the victim's GPS lock on spurious signals. Then, the attacker can manipulate the position of the victim by changing spurious signals. Other advanced strategies, such as nulling, canceling GPS signals by emitting negative signals accordingly [8], could also be used to launch stealthy attacks.

In the aforementioned attack strategies, they mainly focus on how to take over the victim's GPS signals. A recent attack, proposed by Zeng *et al.* [9], utilizes elegantly selected fake position to guide the victim vehicle to drive into a predefined location when the victim is using the navigation system (e.g., Google Map). This attack may be caught when the driver involves but is much more efficient with driverless AVs.

2) *Attacks Against LiDAR*: LiDAR is an active sensing device, and compared with the camera, it can work during the whole day, neglecting the illumination condition. It can also be used to recognize signs, lanes, and so on, since these infrastructures have retroreflective surfaces [14]. With these strengths, almost all of the AVs, excluding Tesla, are armed with LiDAR for circumstance perception [15]. LiDAR senses obstacles around by rotating the transceiver,

emitting infrared lasers, and calculating the distance of obstacles by measuring round-trip time of reflected lasers (see Fig. 3). Several existing works demonstrate that LiDAR is vulnerable to intentional attacks.

Petit *et al.* [16] first introduce an attack targeting at LiDAR embedded in AVs. In their attack, the attacker uses a transceiver to receive the laser pulse sent from LiDAR and relay the received signal to another transceiver, which sends a spurious signal back to the LiDAR after delaying it in a predefined time interval. By controlling the delayed time interval and frequency of sending the spurious signal back, the proposed attack could achieve injecting several obstacles in fixed positions. Later, Shin *et al.* [15] extend Petit's attack, which allows injecting closer fake obstacles. They leverage the fact that the LiDAR scans the environment through rotating laser transceiver and the light travels much faster than the rotating speed of LiDAR. Therefore, the attacker can receive laser pulse in advance and then immediately relay the laser pulse to another transceiver in other angles of LiDAR. This allows the attacker to make fake obstacles closer to him. Besides, they also introduced a jamming attack by sending the same frequency laser to LiDAR.

3) *Attacks Against MMW Radar*: The system structure of MMW radar is very similar to LiDAR, as shown in Fig. 3, except the emitted signal. The MMW radar emits the microwave whose wavelength is longer than laser emitted by LiDAR [17]. Comparing with LiDAR, the MMW radar is robust to poor weather conditions, e.g., storms, fog, and dust [18]. However, due to the longer wavelength of MMW radar, the MMW radar has lower resolution and shorter detectable range. Currently, the MMW radar

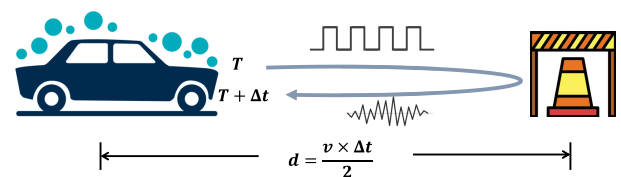


Fig. 3. Working principle of sensors using round-trip time of signal to calculate the distance. Here, v is the speed of the signal in the air (such as sound: 340 m/s and electromagnetic wave and light: 3×10^8 m/s).

is equipped in vehicles of Tesla. In DEF CON 2016, Yan *et al.* [4] demonstrate practical attacks against Tesla Model S leveraging vulnerability of the MMW radar. They conduct experiments on the jamming attack by sending the same waveform signals to the MMW radar to cause lower signal-to-noise ratio (SNR) and, thus, successfully launch the spoofing attack by carefully modulating signals similar to the MMW radar. In their study, it is concluded that the experimental result is prominent, especially when Tesla works on the autopilot mode. As for AVs merely relaying on the MMW radar to achieve obstacles recognition and collision avoidance, it is indeed a nontrivial threat.

4) *Attacks Against Ultrasonic Sensor*: The ultrasonic sensor transmits and receives the ultrasound that is sound waves with high frequencies that human beings cannot hear. Normally, most people cannot sense the sound with a frequency higher than 18 kHz [19]–[21]. It leverages the propagation time of reflected ultrasonic pulses to calculate the distance to the nearest obstacles (see Fig. 3). In AVs, this capability enables ultrasonic sensors to be used for automatic or semiautomatic parking. Similarly, spoofing and jamming are two kinds of attacks threatening the ultrasonic sensor.

The spoofing attack tries to utilize the carefully crafted ultrasound to create a forged obstacle. In [4], the spoofing attack can create pseudo-obstacles when there is no real one in the detection range. Conversely, if there are more obstacles, this attack can easily cause confusions during AV's decision-making procedures. Beyond this work, Xu *et al.* [22] further demonstrate the effectiveness of the adaptive spoofing attacks by creating virtual obstacles against off-the-shelf sensors as well as those onboard ones equipped by AVs.

Simpler but still threatening, jamming attack aims to decrease the SNR of ultrasonic sensors by continuously emitting ultrasound. In [4] and [22], Audi, Volkswagen, Tesla, and Ford are tested, and the result shows that jamming attack can mislead the cars when the driver does not receive any warning about obstacles. Another experiment in [22] shows that jamming attacks work effectively against Tesla cars in the self-parking mode as well as those in the summon mode. In both cases, the jammed car may ignore and hit obstacles.

Moreover, the approaches of acoustic quieting, such as cloaking and acoustic cancellation, can be used for ultrasonic sensor attacks.

5) *Attacks Against Camera*: In AVs, cameras are used in many scenarios, such as traffic sign recognition [33], lane detection [34], and obstacle detection [35]. Fatal accidents may occur when the performance of the cameras is significantly degraded, which is caused by attacks against the cameras.

Petit *et al.* [16] get the efficiency of blinding MobilEye C2-270, a commercial camera system, with several light sources. It shows that leveraging a laser or LED matrix could blind the camera. Petit *et al.* also prove that in the

laboratory environment, the attacker could continuously switch the light ON and OFF to confuse the camera.

Yan *et al.* [4] successfully blind the camera by aiming the LED and the laser light at the camera directly. In particular, aiming the LED light at the calibration board, which is a substitute for realistic scenes, would lead to the concealment of specific areas. According to the results, radiating a laser beam, even for just a short period of seconds in very close distance (less than half a meter) against an AV's camera, would cause irreversible damage and, thus, disrupt the corresponding autonomous procedures.

B. Defense Strategies

In this section, we list countermeasures proposed against attacks of sensors. Table 2 presents a summary of defense strategies against attacks aiming at different sensors. Detailed descriptions of these strategies are introduced as follows.

1) *Defense Strategies for GPS*: Numerous countermeasures have been proposed to prevent GPS-targeted attacks.

For instance, the spurious signals appear different from signals transmitted from the satellites. It could be used to identify GPS attacks. Warner and Johnston [23] detect attacks based on the signal strength, the time interval between signals, and the clock information of signals. Wesson *et al.* utilize distortions of correlation function in the receiver to identify validity of GPS signal [24]. Other works [25]–[29] check the direction of arrival (DoA), which uses the antenna array to alleviate the attacks since DoA of GPS signals would show a distinct carry phase compared with spoofing signals.

Other methods introduce cryptographic techniques into GPS signals for attack defense. O'Hanlon *et al.* [30] propose to encrypt GPS L1 P(Y) code to judge whether a spoofing attack is happening. Authentication strategies [31], [32] are also proposed to ensure that the signals are authentic, e.g., the navigation message authentication (NMA), which embeds signature in the signal from the satellites.

Alternatively, works in different fields of study can be combined to achieve protection, such as distance-bounded protocol [36], [37]. They measure and ensure the distance between entities using cryptographic tools or computer vision techniques by comparing road signs and buildings of the current position.

2) *Defense Strategies for LiDAR*: To resist attacks targeting at LiDAR, Shin *et al.* [15] and Petit *et al.* [16] list the following defense strategies.

Modifying how LiDAR emits and receives laser is a promising way. If the attacker wants to perform attack successfully, the spurious laser should be synchronized with the laser from LiDAR. Emitting laser pulse multiple times (such as three times) in one direction is efficient against an attacker who is not in sync with the laser of LiDAR. In addition, since LiDAR only accepts laser from

Table 2 Summary of Defense Strategies of Attacks Against Sensors

| Defense strategies | | Principle | Modification | Extra hardwares | Reference |
|--------------------|----------------|--|---------------|-----------------|------------|
| GPS | Signal check | Checking signal inherent characters (like strength) | No | Case dependent | [23]–[29] |
| | Cryptography | Encryption and authentication | Signal | No | [30]–[32] |
| LiDAR | Redundancy | Multiple LiDAR | No | Yes | [15], [16] |
| | Fusion | Multiple kinds sensors | No | Yes | [15], [16] |
| | Modification | Reducing receiving angle, pulsing laser multiple times, shortening pulsing time interval | Device | No | [15], [16] |
| | Randomization | Randomly rotating or pulsing signal | Device/Signal | No | [15], [16] |
| MMW Radar | Sanity check | Impossibility of high-power microwave in real world | No | No | [4] |
| | Redundancy | Multiple MMW Radars | No | Yes | [4] |
| | Fusion | Multiple kinds sensors combination | No | Yes | [4] |
| | Randomization | Randomly pulsing signal | Signal | Yes | [4] |
| Ultrasonic sensor | Sanity check | Impossibility of high-power ultrasound in real world | No | No | [4] |
| | Redundancy | Multiple ultrasonic sensors | No | Yes | [4], [22] |
| | Fusion | Multiple kinds sensors combination | No | Yes | [22] |
| | Randomization | Randomly pulsing | Signal | Yes | [22] |
| Camera | Redundancy | Multiple cameras cooperation | No | Yes | [16] |
| | Special optics | Filter and photochromic lenses | Device | Yes | [16] |

a specific angle during rotating, reducing receiving angle can mitigate the effect of attacks, but it is also a tradeoff of LiDAR's sensitivity [38]. Another countermeasure is to reduce the LiDAR receiving time, which reduces the probing range of LiDAR. To ensure certainty, LiDAR defines the receiving time, within which LiDAR receives incoming lasers. Specifically, reducing receiving time leaves fewer chances for an attacker to perform attacks but also enables the lasers, which is reflected from a further object, to be taken invalid.

Another strategy is to introduce randomness while LiDAR is working. Since LiDAR rotates the transceiver for scanning circumstance around, LiDAR is designed to rotate in a random speed and emit laser to a random direction to prevent attacks proposed by Shin *et al.* [15]. In addition, making laser from LiDAR more unpredictable by emitting randomized signals or emitting signals in a random pulse interval is another efficient way against attackers.

Finally, redundancy of LiDARs or multisensor fusion allows AV to correct readings of LiDAR(s). It increases the cost and complexity of the attacker and, meanwhile, introduces extra cost to customers due to installing new devices. In addition, in the nonoverlapped area, the attack can still be launched [15].

3) *Defense Strategies for MMW Radar*: Yan *et al.* [4] gave a discussion about how to confront attacks toward radar. First, they believe that the jamming attack is easily detectable since the jamming-like signal is rare in the real world. When the radar detects such signals, there is a high possibility that radar is under attack. Then, for resisting spoofing attacks, they recommend introducing randomness into radar's signal. Finally, they suggest sensor fusion strategy, namely, using different sensors reading to correct each other.

4) *Defense Strategies for Ultrasonic Sensor*: In [22], two approaches are proposed to defend against ultrasound sensor attacks. The first one leverages the idea of shifting

the parameters of waveforms and, thus, makes it possible to authenticate the physical signals. The second approach uses two or more sensors to detect attacks, recover the abilities of obstacle detection, or localize attackers. According to the experiment, the two countermeasures can effectively defend against ultrasonic sensor attacks.

5) *Defense Strategies for Camera*: Because of the vulnerability of the camera caused by optical characteristics, it is difficult to build a completely secure camera system. Nevertheless, Petit *et al.* [16] give some possible countermeasures. Redundancy, removable near-infrared-cut filters, and photochromic lenses can provide proper protection from different aspects despite the fact that they may have limitations or introduce new problems.

III. POTENTIAL THREATS OF IN-VEHICLE SYSTEMS

To facilitate the access control of the automated vehicles, it is possible to deploy certificates to support the authentication of the controllers. Next, we present the potential security threats related to the in-vehicle access control systems, including vehicle immobilizer, keyless entry systems, control components, and VCSs. After that, we investigate the countermeasures of the vulnerabilities.

A. Various Types of Attacks

Here, we introduce the attacks that target the in-vehicle authentication systems.

1) *Vehicle Immobilizer Attack*: As a common antitheft device, the electronic vehicle immobilizer realizes electronic security to prevent the start of the vehicle engine, unless the corresponding key fob, also known as a transponder or physical security token, is used. In recent years, quite a few widely used transponders in-car immobilizer industry are discovered as insecure [39]–[42]. Table 3 shows the characteristics and vulnerabilities of these

Table 3 Representative Targets of Vehicle Immobilizer Attacks

| Target name | Security scheme | Vulnerabilities | Type of attack | Reference |
|--|-----------------------------------|--|-----------------|-----------|
| Digital Signature System | Challenge-response protocol | Short secret key | Spoofing | [39] |
| Passive Keyless Entry and Start system | LF RFID tag | Passive, fake proximity | Relay | [40] |
| Hitag2 | 48-bit LFSR & a non-linear filter | malleability, lack of PRG | Key-recovery | [41] |
| Megamos | 96-bit secret key & PIN code | malleability, lack of PRG, invertibility | Key-recovery | [42] |
| Security protocol stack | AES | Key storage method | Fault injection | [43] |

schemes. Among them, Hitag2 and Megamos are both broken due to the weaknesses in the designs of the cipher [41], [42], including the lack of pseudorandom number generators (PRGs) and the shortness of cipher's internal states, in comparison with the private key. In [41], vulnerabilities of the Hitag2 cryptographic scheme are revealed, and three crypt-analytic attacks are proposed to retrieve the private keying materials. By exploiting the malleability of the cipher and the lack of a good-quality PRG, the first attack manages to read the identity of the transponder and recover keystream. The second attack is more generic, which can be utilized to break the generic cipher designs using linear feedback shift registers (LFSRs). It is used to bypass the read protection mechanism from the security token, and still, it successfully retrieves the private keying materials in just 60 s. The final attack attempt leverages the key observation that there are dependencies across different authentication sessions with the immobilizer of the car. Such dependencies can also be exploited to extract the private keying materials although at a slightly lower rate, in the order of minutes, compared to the second attack.

Similar to [41], three attacks aiming at Megamos are proposed in [42]. Apart from the vulnerabilities mentioned earlier, the first attack leverages two new observations for the retrieval of the private keying materials: 1) the cipher state successor can be invertible and 2) the multistep authentication protocol reveals bits of plaintext in the final steps. The second attack simply uses the publicly known default personal identification number (PIN) code to retrieve the private keying materials within a timeframe of half an hour. Moreover, the attacks in both [41] and [42] use time-memory tradeoff (TMTO) to reduce the time cost of secret key retrieval from days to hours, minutes, and even seconds.

In 2010, an open protocol stack for the security of the car immobilizer system was proposed. It controls the authentication functionality and uses off-the-shelf AES encryption. Security vulnerabilities of the protocol stack are theoretically analyzed in [53], and there are several types of implementation attacks [43], [54], [55]. Tillich and Wójcik [53] discuss the possibility of several attacks, including relay attacks, tracking, denial-of-service

(DoS) attacks, replay attacks, spoofing attacks, and hijack of the communication sessions.

Apart from the potential vulnerabilities discussed in [53], Takahashi and Fukunaga [43] propose an invasive fault attack, which exploits the secret key storage specifics of the security protocol stack. Specifically, the secret key is replicated three times in the key fob storage space.

For key fob authentication, all three copies of the secret keys are used one by one, thus enhancing the robustness and the availability of the immobilizer system. However, through fault injections, the adversary can alter a part of the data at the physical address of the very first secret key while trying out the remaining part of the secret key. By repeating the process of fault injection and guessing with the other two secret keys, the adversary can retrieve most bits of the secret key for AES and eventually retrieve the entire secret key with exhaustive search.

2) *Keyless Entry Systems Attack*: While the vehicle immobilizer system focuses more on starting the engine, the attacks toward keyless entry systems mainly aim to break into the car.

Entry system guarantees the safety of the properties inside the vehicle. With technological development, there are three types of car keys: 1) traditional physical key; 2) remote active keyless entry; and 3) remote passive keyless entry and start (PKES). Features of the systems are shown in Fig. 4. The earliest physical key only allows physically unlocking the door and starting the engine. The key should be inserted into the lock hole, and there is no electrical communication between the key and the vehicle. The remote active keyless entry system is embedded into a key fob. "Active" means that there are interactions between

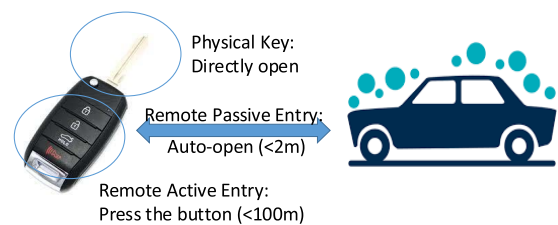
**Fig. 4.** Characteristics of typical entry systems.

Table 4 Characteristics of Typical Attacks Against Keyless Entry Systems

| Attack type | Vulnerable system | Implementation complexity | Countermeasure | Defense complexity | Reference |
|------------------------|-------------------|---------------------------|------------------------|--------------------|------------------|
| Jamming | All remote | Easy | Be careful | Easy | [44]–[47] |
| Replay | Fix-code remote | Medium | Cryptography | Easy | [44], [48], [49] |
| Relay | Passive remote | Hard | Electromagnetic shield | Medium | [40], [44] |
| Cryptographic analysis | Active remote | Hard | Improve cryptography | Hard | [50]–[52] |

the user of the key fob and the entry system. When opening/closing the vehicle's door, the user needs to press a button to generate signals from a radio-frequency (RF) transmitter. Then, the car receives the signals and authenticates the data with cryptographic methods. However, some users may find searching for the key and pressing the button disturbing. The remote PKES system solves this problem by realizing keyless entry. In this system, the user only needs to approach the car and the door will open automatically. Moreover, the PKES also supports automatic engine start, which means that when the driver is seated, the engine is activated. The communication between the key and the car relies on an LF RFID tag for short-distance (≤ 2 m) autoentry and start and a full-fledged ultrahigh frequency (UHF) for remote-distance (≤ 100 m) door unlocking.

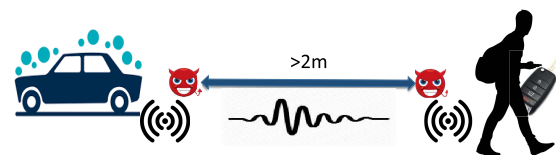
Here, we list several possible attacks on the keyless entry systems. The features of the attacks are presented in Table 4.

Jamming Attacks: Due to the wireless communication between the key and the car during the opening or closing process, there are chances for the adversaries to jam the signal when the user closes the door. When the user presses the “close” button, the attacker can generate an interference signal to jam the locking signal. The user is unaware of the fact that the door remains unlocked and leaves so that the attacker can break-in. This method is reported in the news [45]. Technically, the jamming method could be regarded as intentional electromagnetic interference (IEMI) [47]. Beek *et al.* [46] carry out a detailed robustness study against interference through a series of experiments about systems with such keyless entry. According to their experiment setting, the key fob is 2 m away from the car, and continuous-wave interferences with the range from 420 up to 460 MHz are generated to test the robustness of the original signals. Results show that the two keyless systems in their experiment are sensitive to interference with a bandwidth of 5 and 4 MHz, respectively, and the interference can be generated at a distance of 100 m, which provides convenience for attackers. Furthermore, the jamming attack does not require any cryptographic or chip analysis, making it easy and cheap to launch.

Replay Attacks: A typical scenario of replay attacks is that the thief eavesdrops and records the back and forth signal exchange between a common key transponder and a corresponding receiver on the car. For an unsupervised car, the attacker can replay the recorded signal and open the door. However, this kind of attack is not effective for

most of the latest car models because of the adoption of rolling code for the key fob. In short, the rolling code keeps an incremental counter, and the encrypted code will change whenever the button is pressed, which makes sure that an attacker cannot easily guess the code and replay it. Nevertheless, replay attacks could be integrated with other attacks. For example, the attacker can jam and record the valid “close” code and then replay the code after a break-in, after which the car is appropriately locked. Furthermore, the attacker can keep eavesdropping, jamming, and recording the valid signals until she gets the expected signal (e.g., the owner gets frustrated when keeping failing to open the door and leaves, as described in [48]), and then the attacker can record the latest valid “open” code and open the car [49].

Relay Attacks: Relay attacks have been widely researched and are prevalent within communication systems [56]–[58]. A relay attack can break the distance restriction in the communication system by placing devices between the signal sender and receiver and relaying the signals between them. As for our topic, the remote PKES system enables the car owner, without looking for a key, to unlock the car, which is convenient, however vulnerable to relay attacks. Recall that in a PKES system, when the key is near the car, e.g., 2 m, the door will passively open. Moreover, when the receiver detects that the key is inside the car, the engine starts and then the driver can step on the gas and go. Nevertheless, the protocol only depends on the communication signals, not on the physical key. Alrabady and Mahmud [44] first exploit this weakness and described a two-thief model conceptually. Later, Francillon *et al.* [40] follow the idea and launched the relay attack on the PKES system. The attacker places an antenna close to the car door and another antenna near the car owner, and then, the antennas can transfer the signals, as shown in Fig. 5. Although physically the distance between the key and the door is not short enough to complete the protocol, the signals from the key transferred by the antennas fool the receiver in the car and the challenge–response protocol

**Fig. 5.** Model of relay attack.

can complete. In their experiments, the attack is effective when the key-side antenna is within 8 m (in the best situation) from the key and the distance of the antennas can be up to 3000 km, which is practically effective. A typical scenario introduced by the authors is that in the parking lot, say, when the car owner leaves the parked car, the car becomes unsupervised and often out of sight. After that, one attacker attempts to move the car-side antenna close to the door, and the other attacker with key-side antenna can tail after the owner. In this way, it is possible to establish the relayed communication between the key fob, which is with the owner, and the parked car, which is away from the key. Such communication could work as if the key and the car are spatially close. Note that this relay attack does not need to interpret or manipulate the signals, and thus, the cryptographic authentication could not help in such scenarios.

Cryptographic Analysis Attacks: The aforementioned attacks mainly aim at physical-layer communication, and they do not consider the analysis of the signals. Another line of attacks can be described as cryptographic analysis attacks against the encryption and code algorithms in higher layers. The earlier generation of the remote keyless system does not provide an authentication mechanism. The code is fixed, and cryptography is not involved. To enable authentication, in [63], the authors propose to use rolling code techniques that are effective in defending against the most straightforward replay attack. However, the Keeloq scheme is proven to be insecure against cryptographic analysis [50] and side-channel attacks [51]. Apart from the inherent vulnerability in cryptographic protocol, the printed circuit boards (PCBs) in the entry systems can also be analyzed by attackers to steal the information in the firmware. A solid research [52] investigates the widely used VW group remote control systems and succeeds in cloning a targeted remote control by analyzing the cryptography used in the schemes and eavesdropping the signals of the victim, after which the adversary can break into the car. The attack takes advantage of the vulnerability that most remote control systems share the same master key. If the attacker gets the PCBs and takes a deep insight into the firmware, there are chances that she can figure out the structures of the codes, the details of the cryptographic algorithms, or even the encryption key. With the global used master key, the attacker can then get the counter by eavesdropping and decrypting the signal from the victim. The authors also propose an attack on Hitag2. The correlation attack can recover the secret key in minutes.

3) **VCSs Attack:** VCSs are widely applied in in-vehicle access control and the enhancement of the driving experience. As shown in Fig. 6, usually, a VCS is constructed of three basic modules: 1) the voice capture module that records the ambient voices and digitalizes it before the next stage; 2) the speech recognition module that operates on the digitalized signals and uses machine-learning tech-

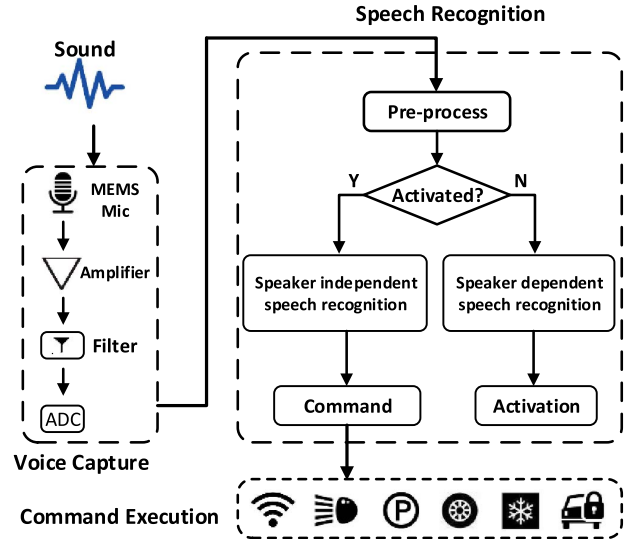


Fig. 6. Architecture of a typical VCS that takes voice commands as inputs and executes corresponding commands.

niques to further understand the instructions; and 3) the command execution to perform the designated command. Recently, researchers focus on the inaudible voice attacks that are incomprehensible to humans but recognizable to VCS as commands, thus control the systems without being detected [59]–[62]. The attack schemes are summarized in Table 5.

Zhang et al. [60] propose DolphinAttack that exploits the hardware properties of the audio circuits to insert hidden voice commands that are inaudible by the human. The key idea of DolphinAttack is to modulate the regular voice signal, which is often at low-frequency band, on a UHF carrier, also known as an ultrasonic carrier. Doing so ensures the inaudibility of the voice commands. Therefore, amplitude modulation is utilized to exploit the nonlinear property of microelectromechanical systems (MEMS) microphones that can downconvert high-frequency signals to lower frequencies. Thus, with a carefully designed input signal, the microphone with nonlinearity can recover the wanted voice control signal. Though effective on major speech recognition systems, DolphinAttack [60] requires vicinity to the target devices, e.g., the attack can be launched from a distance of 5 ft to Amazon Echo. This is because the speaker with the same nonlinearity can also produce audible lower frequencies while playing the higher frequencies. Thus, DolphinAttack must be operated at low power, which constrains the range of the attacks. To enlarge the range of a successful breach, the inaudible attack system, LipRead, is devised in [61]. To tackle the contradiction between the long range and inaudibility, the authors use multiple speakers. The “signal leakage” from an individual speaker is limited to a narrow low-frequency band. By solving the min-max optimization problem, the aggregated leakage can be kept under the human auditory response curve. Following this method-

Table 5 Hidden Voice Attack Techniques

| Attack name | Method | Attacker's knowledge | Range | Inaudible (Y/N) | Reference |
|----------------------------|------------------|----------------------|-----------|-----------------|-----------|
| Hidden voice commands | Machine learning | Black & white box | < 3.5m | N | [59] |
| Dolphin Attack | Hardware | White box | 2cm~175cm | Y | [60] |
| Lipread | Hardware | White box | < 8m | Y | [61] |
| Audio adversarial examples | Machine learning | White box | N/A | N | [62] |

ology, the maximal attack distance is improved to 8 m in [61]. Furthermore, the researchers also propose effective defense mechanisms against such attacks, through identifying nonlinearity traces, which is a feature often preserved in signals with commands of hidden voice. In spite of their efficiency and innovation, both DolphinAttack [60] and LipRead [61] require the attack devices to emit ultrasound signals [64], which means that the adversary must carry a customized device. Since the range of the inaudible voice command attack is still restrained, the transmitter that produces special signals could still be noticed by the targeted victim. This limitation hinders the feasibility of the hidden voice command attacks.

B. Defense Strategies

There are several possible strategies to defend the aforementioned attacks. The physical-layer attacks, especially the attacks based on signal interference and signal transmission, can be easily prevented by intentionally paying more attention, where the countermeasures can be carried out by individuals. More complicated defenses include cryptographic update, extra authentication, scheme modification, and so on. Here, we introduce these defenses and encourage readers to explore more countermeasures.

1) *Leave With Caution*: The simplest way to prevent the jamming attack is to make the car owner assure that the door is locked before he/she leaves, as advised in [65]. For remote confirmation, light or sound could be used to indicate that a car is locked properly. However, the countermeasure is only effective for the jamming-only attack. If the attacker can replay the “unlock” signal, the door will lock appropriately and the remote confirmation method becomes insufficient. Hence, the basic countermeasure is to make sure that the doors are locked before moving away from the vehicle.

2) *Block the Source Signal*: An instant way to avoid relay attack is to shield the key when it is not being used [40]. If the key is shielded by a box, the antenna on the key side cannot receive and transmit the signal from the key fob. However, this method brings inconvenience to the user because when he/she wants to get into the car, he/she needs to take out the key, which disables the most attracting advantage of the passive remote keyless system. A similar countermeasure is to remove the battery from the key so that the key will not send and receive signals. Also, this method impacts the functionality of PKES.

3) *Distance Bounding*: Distance bounding is a helpful method to defend against the relay attack [57], [66],

[67]. In a distance bounding algorithm, rapid exchanges of messages are conducted in order to verify the distance between the parties. The door will open automatically only if the distance between the key fob and the car is proven valid. Francillon *et al.* [40] give the sketch of the distance bounding solution to deal with relay attack on PKES and discussed the implementation details. The reason that the relay attack can work is that the antennas can transfer the signals even if the parties are distant. However, this may bring latency, and a long latency is not allowed in a distance bounding protocol.

4) *Authentication Improvement*: Quite a few attacks on the vehicle immobilizer and the keyless entry systems are aiming at cracking the cryptographic protocols. One solution is to improve the authentication mechanism. In other words, a more secure cryptographic algorithm and key distribution method should be used in nowadays remote keyless entry (RKE) systems. Fortunately, Moradi and Kasper [68] have already presented a more secure RKE architecture, which can resist side-channel attacks. To improve the security level for the control systems in practice, vehicle manufacturers may make efforts to implement the state-of-the-art secure mechanism on the new-designed cars.

5) *Hidden Voice Detection*: To prevent VCS against hidden voice commands, various strategies have been introduced, including device enhancement, signal analysis [60], audio turbulence [69], [70], and liveness detection [71], [72].

As introduced in Section III-A3, in its principle, the attacks on VCS use the electronic devices to produce inaudible voice commands, while the normal commands of controllers come from live speakers. With this observation, the general defense is to analyze the signals via standard signal processing techniques, thus differentiating the attack signals from the normal ones. As introduced in [60], concrete methods in this line of work can be classified as hardware-based ones and software-assisted ones. A typical hardware-based approach would be producing command cancellation. While on the software level, it is also possible to extract unique features from signals. In [69], similar ideas are discussed in the name of audio turbulence and audio squeezing.

In [71], a specific method with targeted scenarios is elaborated. Their basic idea is to identify the sound source. On that account, the authors devise a liveness detection approach by leveraging the pop noise. For instance, the pop noise could be an explosive burst caused by the breath of a live speaker. When replayed by a speaker, the adversarial

Table 6 Comparison of In-Vehicle Protocols

| Bus | CAN | LIN | FlexRay |
|----------------|---|--|--|
| Applications | Engine control, airbags, antilock break system, body system | Body control(dorr locking, lights, seat belts) | Multimedia and X-by-wire (drive-by-wire, brake-bywire, steering-by-wire) |
| Data Rate | 1 MBit/s | 20 kBit/s | 10 MBit/s |
| Exposure | Big | Little | medium |
| Architecture | Multi-Master | Single-Master | Multi-Master |
| Access Control | CSMA/CA | Polling | TDMA |
| Kind | Event-triggered | Subbus | Time-triggered |
| Redundancy | None | None | 2 Channels |
| Transfer Mode | Asynchronous | Synchronous | Asynchronous/Synchronous |
| Physical Layer | Dual-Wire | Single-Wire | Optical Fiber Dual-Wire |

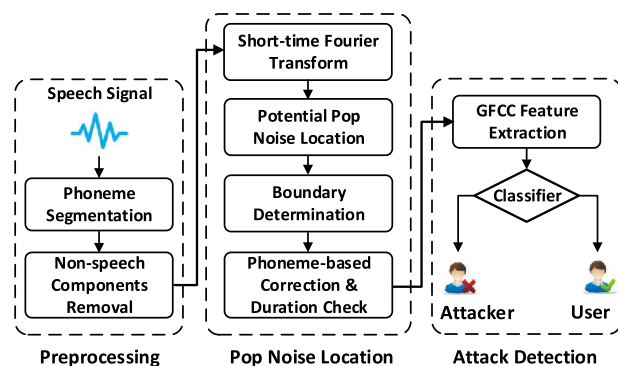
audio cannot reproduce the burst of airflow without real human breath. Hence, the pop noise can be used to distinguish the adversarial audio from live commands. As shown in Fig. 7, the defense scheme consists of three different phases: preprocessing of signal, the location of pop noise, and the detection of the attack.

IV. POTENTIAL THREATS OF IN-VEHICLE PROTOCOL

With more and more requirements on automobiles to pursue a comfortable and smart driving environment, the number of onboard electronic devices increases dramatically, in which electronic control units (ECUs) are most significant. Hence, the communications of ECUs are becoming more and more complex. It is vital to take into account the security of in-vehicle network communications [73], for example, in the LIN, the CAN, or the FlexRay. We present a brief introduction and comparison of CAN, LIN, and FlexRay in Table 6. It exposes vehicles to various attacks. Attackers can take arbitrary control of multiple vehicles or even kill them with a remote connection. Moreover, AVs exacerbate these threats because of the lack of human driving and monitoring. This section presents the most recent in-vehicle network attack and defense methods.

A. Various Types of Attacks

The in-vehicle protocols, including CAN, LIN, and FlexRay, have drawn much attention from the attackers.

**Fig. 7.** Detection scheme based on the pop noise.

In particular, the research on the security of CAN bus has received extensive attention. Recent studies have demonstrated that many attacks have been launched against in-vehicle protocols, such as spoofing and DoS. We comprehensively analyze and introduce these attacks on CAN, LIN, and FlexRay protocols.

With the increase of onboard electronic devices, CAN protocol began the dominant communication method of motor vehicles. CAN bus is famous for its advantages of multiple masters, low cost, and high transmit rate [74]. However, CAN protocol was designed without security consideration at the beginning, and thus, it is vulnerable to some attacks, such as injecting false messages into CAN bus. Five major security threats inherent in the CAN protocol are as follows.

- 1) *Broadcast Nature*: CAN protocol broadcasts the packet into all nodes. Hence, all packets can be snooped by the malicious node, which paves the way for malicious attacks on CAN, such as replay attacks.
- 2) *No Authenticator Fields*: Without authenticator fields, a node cannot tell whether a packet is from a malicious node. Thus, malicious nodes can easily impersonate other nodes and tamper with data.
- 3) *No Authenticator Fields*: Without authenticator fields, a node cannot tell whether a packet is from a malicious node. Thus, malicious nodes can easily impersonate other nodes and tamper with data.
- 4) *Defective Arbitration Scheme*: The CAN protocol utilizes the carrier sense multiple access with collision avoidance (CSMA/CA) methods and the priority-based arbitration scheme. Hence, malicious nodes can achieve the DoS attack by repeatedly playing the high-priority message.
- 5) *Dangerous Interface*: The most dangerous and significant interface is the onboard diagnostic (OBD)-II port, and it is also a federally mandated port in the United States. Then, the CAN bus is accessed directly via the OBD-II port, which is used for reprogramming and diagnostic. These properties have abstracted much attention from many attackers.

Moreover, researchers show that CAN bus is more vulnerable than we expected. Koscher *et al.* [75] demonstrate that the attacker could be in control of many automotive functions, e.g., it can stop the engine, disables the brakes,

Table 7 Different Studies Related to Attacking on CAN

| Access Method | Attack Method | Attack Vehicles | Attack Results | Year | Reference |
|---------------|---------------|---------------------------------|--|------|-----------|
| Direct Access | Spoofing | - | braking, stopping the engine, disable the brakes | 2010 | [75] |
| | | Ford Escape and Toyota Prius | steering, acceleration, braking and display | 2013 | [76] |
| | DoS | Honda Accord and Hyundai Sonata | shutting down healthy ECU | 2016 | [77] |
| Remote access | Spoofing | - | controlling brakes, engine, locks, uploading firmware, and exfiltrating data | 2011 | [78] |
| | | Jeep Cherokee | steering, braking | 2015 | [79] |
| | | Tesla Model S and Model X | compromising CAN bus, achieving arbitrary code execution | 2017 | [80] |

brakes the wheels, and changes the display, by directly injecting false CAN message through OBD-II. As the automotive driving system gets smarter, it has more and more I/O interfaces and is, therefore, potentially vulnerable to attack. Checkoway *et al.* [78] comprehensively analyze the vehicle attack surface. It empirically demonstrates that the postcompromise I/O interface can be remotely triggered to control any vehicle function and filtering data. Similar to [76], the design of [77] can control the steering, acceleration, braking and display on Ford Escape and Toyota Prius.

However, in the aforementioned attack methods, in order to control the vehicle at will, reverse engineering is required to understand the meaning of packets. However, reverse engineering is hard and relies on different vehicles. Cho and Shin [77] present a new kind of DoS attack, called the bus-off attack, exploiting the error-handling method that automatically isolates misbehaving or defective ECUs in CAN protocol. Specifically, bus-off attack iteratively injects false messages to deceive a healthy ECU into believing itself defective. Finally, it can trigger the CAN fault confinement, forcing the attacked ECU or, more severely, the entire network to close down. This attack does not require reverse-engineering packets that make it easy to mount.

The most famous attack is [79], which leads to a recall of about 1.4 million Jeeps. This is the first time a vehicle has been attacked through a remote connection without direct access to the bus. Nie *et al.* [80] remotely attack the Tesla model by utilizing a complex chain of vulnerabilities, including previous vulnerabilities in the IT field. We summarize the above-mentioned attacks in Table 7.

1) *Local Interconnect Network*: The LIN bus is an inexpensive serial communications protocol, which is intended to complement the CAN bus. The LIN bus is commonly used for vehicle body control, such as seats and doors. Although the threat of the LIN bus attack is not as significant as that of the CAN bus attack, it also poses considerable security risks to high-speed cars. A brief introduction about security on the LIN bus is provided [81].

The LIN bus is broadcast and comprises master-slave nodes (one master and typically up to 15 slaves). The master node initiates a header containing the identifier (ID), and at most one slave node replies to the given identifier. Because the master initiates all communication, it is not necessary to implement a collision detection algorithm. Hence, the defective error-handling mechanism is used to attack the LIN bus [82]. In the LIN error-handling mechanism, the normal sender node stops the packet transfer when the collision is detected. It creates an opportunity

for the malicious nodes to send a false message to replace the valid one.

2) *FlexRay*: FlexRay has a reputation for next-generation automotive communications protocols, but it is not used as a replacement for CAN bus and LIN bus. It meets the future communication demands of high data rates, low-cost, high stability, and flexible data communication. FlexRay is a time-triggered protocol. It employs time-division multiple access (TDMA) in order to prevent bus contention and achieves real-time redundant communication. Like the CAN bus, FlexRay bus also lacks data confidentiality and authentication mechanism. Hence, it is easy to perform the read and spoof attacker action [83].

B. Defense Strategies

As mentioned earlier, CAN has some major limitations. Therefore, most current defense methods are to circumvent these limitations.

1) *Gateway Installation*: Gateway is a common and effective defense method. Wolf *et al.* [84] introduce the gateway in the automotive bus system. Within the in-vehicle network, the central gateway-based architecture has been transformed into a backbone-based architecture [85]. The gateway transfers the message from various ECUs, which also provides the functions of protocol conversion, message verification, and error protection. It acts as the interface for vehicle communication. In addition, the gateway also includes the firewall mechanism, which increases the difficulty of access to the bus through vehicle attack surfaces. For example, the attack message cannot be directly injected into the in-vehicle bus by the OBD-II port. The gateway can manage the data transmission between the low-speed bus and high-speed bus.

2) *Encryption Scheme*: One of the necessary steps to enhance bus communication security is to encrypt data transmission. Wolf *et al.* [84] utilize cryptographic tools and present a secure communication scheme for automobiles that combined symmetric and asymmetric encryptions to achieve high performance and adequate security. Yu *et al.* [86] present encryption and obfuscation techniques to prevent code tampering and data sniffing. The obfuscation is a cost-effective method against reverse engineering. Moreover, to effectively encrypt the data transmission between the external memory and the ECU internal memory, the on-the-fly decryption is introduced. Woo *et al.* [87] utilize AES-128 and keyed-hash MAC together for encryption and authentication, finally reducing the bus load.

3) *Authentication Mechanism*: Nilsson et al. [88] present delayed data authentication using MACs. However, problems associated with the communication cost also arise. A vote-based technique [89] integrated with time-triggered authentication is proposed to reduce authentication latency and improve bandwidth efficiency. This technique uses unanimous voting on the message validity and value among a set of nodes to decrease the probability that a per-packet forgery succeeds. Instead of independently authenticating each node, Groza et al. [90] present the lightweight broadcast authentication protocol (LiBrA-CAN) that splits the authentication key between any two groups of nodes. The assumption that the compromised nodes are only a minority is practical. MAC is considered on the AUTomotive Open System ARchitecture (AUTOSAR) in 2017. MAC can effectively prevent unauthorized CAN messages because the attackers do not have the authentication key. However, the attack on MAC is implemented [91].

Moreover, the error frame transmission [92]–[94] is proposed to prevent unauthorized CAN message. The basic idea is that when a node detects an unauthorized message, the node sends an error frame immediately to override it before the receiving node receives it.

4) *Anomaly Detection*: Anomaly detection [95]–[97] on CAN is developed from anomaly packet detection on the Internet. Larson et al. [98] introduce security specifications for ECU behavior and communications and presented some example specifications. Müter et al. [99] introduce a batch of sensors of different types for anomaly detection to detect the characteristics of in-vehicle networks, such as frequencies and load. As most normal CAN packets arriving at a fixed frequency, Taylor et al. [100] propose an interpacket timing measurement algorithm over a sliding window. The following support vector machine (SVM) can detect anomalies with satisfying results. Moreover, some works utilize the inimitable physical characteristics of the message, including voltage and signal, to achieve authentication and detect malicious ECU [101], [102], [102].

V. FUTURE DIRECTIONS

Fully automated driving, which can operate on any road at any time with no human interaction [103], has been viewed as the holy grail of AVs that would vastly revolutionize the industry of automotive and bring engaging transporting experience in our daily life. Recently, the success of self-driving systems based on deep-learning algorithms has, for the first time, shed light on a practical and very promising direction for achieving such an ultimate goal. In general, such a system consists of a trained machine-learning model and many advanced sensors. The trained model serves as the brain for the vehicle to “see, hear, and make reasonable driving decisions” all on its own. Though it is intriguing and convenient to delegate all of the control rights to the vehicle itself, fatal incidents

could also occur if the self-driving system goes wrong. In addition, updating the self-driving system requires new incoming training data from the vehicle, which potentially leaks information about the daily routine as well as other private information. This section first summarizes and discusses the new severe threats in the future generations of AVs, i.e., fully automated self-driving vehicles. Then, it provides possible defense strategies to make fully automated self-driving vehicles safer.

A. New Security Threats

We now introduce the new security threats in fully automated self-driving vehicles.

1) *Trained Model Errors*: Self-driving vehicles rely on a deep-learning model-based perception system to identify objects and drive autonomously on their own. However, due to algorithm bugs or model errors, the perception system in a self-driving vehicle may misclassify objects and lead to fatal car incidents [104]. One recent example is the Uber self-driving vehicle incident [104], [105]: a self-driving vehicle misclassified a pedestrian as other objects and failed to break in time to prevent the collision. Therefore, the first new threat in fully automated self-driving vehicles would be the errors implemented in the trained deep-learning model. In such a safety-critical system, it is crucial to make sure that the trained model for object identification and classification is robust and bug-free.

2) *Adversarial Examples*: Besides the errors in the trained deep-learning models, misclassification can also be triggered by specially crafted adversarial inputs. This new threat is much more serious than inherent model bugs/errors because an outside attacker can trick the self-driving vehicle to actively deviate from the correct actions by inputting adversarial (image) examples [70], [106], [107]. For example, as demonstrated in a recent work [108], an attacker can deceive a self-driving vehicle by deliberately generating toxic signs alongside the road, causing the trained deep-learning model to misclassify signs and drive recklessly. Consequentially, such a severe threat from adversarial examples, if not carefully addressed, would lead to potentially life-threatening consequences. Moreover, adversarial examples under black-box attack models [109], where no parameter information of the target deep-learning model is required, pose even severer threats to self-driving vehicles. On that account, an attacker could train an adversarial network [110] to generate more advanced adversarial examples for attacking, which makes the defense for adversarial examples more challenging.

3) *Model Training Privacy*: Training an accurate deep-learning model for self-driving vehicles requires a very large data set of road images or real driving videos as learning inputs. Thus, continuously contributing learning inputs collected from self-driving vehicles is essential to

make the deep-learning model robust and accurate in real deployments. However, most current model training infrastructures are centrally structured, which means that the input data from self-driving vehicles are transferred to a centralized server transparently. Since the contributed learning data set is closely related to daily lives, it might reveal sensitive information of people, e.g., routine and locations [111]. Besides, according to a recent study [112], the trained deep-learning models can also leak sensitive information of the data contributors. More specifically, an attacker can leverage the model's memorization of unique or rare sequences in the learning inputs and extract useful information from the trained models. Therefore, how to collect data for model training while preventing privacy leakage needs a thorough study before deploying self-driving vehicles in the real world.

4) *Model Execution Threats*: In the implementation of fully automated self-driving systems, many new designs of hardware, such as tensor processing unit (TPU), GPU, application-specific integrated circuit (ASIC), and field-programmable gate array (FPGA), are incorporated inside the AVs [113] for achieving lightweight and efficient deep learning. Existing systems construct a new central operating component inside the self-driving vehicle for controlling the hardware to work seamlessly without mutual intervention. However, similar to in-vehicle systems, such a central operating component might subject to malicious attacks, e.g., malware injections, and, thus, can hardly guarantee the correctness of model executions. Therefore, such an operating system should be modeled as an untrusted environment whose attack surface may be easily leveraged by the attackers, and advanced defense mechanisms should be deployed for ensuring execution integrity in self-driving vehicles.

B. Defense Strategies

We briefly discuss the strategies for defending against the aforementioned security threats in fully automated self-driving vehicles.

1) *DNN Robustness Improvement*: In order to improve the robustness and reduce errors of deep-learning models, we could conduct comprehensive testing on those trained models. Existing testing of trained models for self-driving vehicles is mostly based on either: 1) measuring and analyzing the recognition error over a newly inputted learning data set or 2) running real driving tests on the road and giving attention to disengagements, i.e., the incidents where the self-driving vehicle cannot decide [104]. In the future, the testing procedures of deep-learning models could be more automatic. When an error is detected, the system can automatically retrain the model for improving accuracy. Also, the testing can be extended to real time so that errors can be continuously monitored during model execution and automatically patched to further enhance driving safety.

2) *Adversarial Example Defense*: To address adversarial examples that can trick the deep-learning model into behaving what the attacker wants, the first possible defense strategy is to preprocess or filter of input data so as to detect and eliminate the adversarial examples before executing. For example, we can use standard blurring techniques, e.g., the Gaussian blur [114], to let our trained model "escape" from adversarial examples. Another useful defense strategy is to generate adversarial examples or detect potential adversarial examples using data mining methods and then retrain the model with these generated adversarial examples to make the deep-learning model more robust. Finally, we can also try to enhance the interpretability of underlying deep-learning models. Using the poison traffic sign adversarial example as an example, we can let the self-driving vehicle give the reasoning of the made decisions, by explaining what it "sees" in the input image [115]. In this way, we can closely monitor the model execution procedures and detect incorrect driving decisions in time to prevent fatal accidents.

3) *Data Privacy Preservation*: To provide privacy of the contributed training data, one possible strategy is to leverage the emerging federated learning architecture [116] to train and update the deep-learning model. With this privacy-enhanced architecture, the sensitive inputs for model training never leave the self-driving vehicles, and only the model parameter updates are sent to the server for model converging and updating. As a result, the private training data from all self-driving vehicles can be protected during the model training and updating process.

Specific configurations could be set to minimize memorization during training to prevent data leakage. In particular, one potential strategy for defending against memorization is by adding the chosen noise carefully to each gradient update during learning so as to make the trained models differentially private [117]–[119]. In this way, we can effectively hide the occurrence of some private information in the trained models and can, thus, prevent an attacker from extracting them by abusing model memorization.

4) *Execution Integrity Enhancement*: To enhance the execution integrity inside the self-driving vehicle, we can leverage trusted execution enclave (TEE) [120] to construct a secure and isolated environment for executing integrity-critical driving decisions and learning. Currently, available TEE constructions are implemented in CPUs manufactured by Intel [121] and AMD [122]. In the near future, we can further design enclaves for new hardware, from GPUs to ASIC circuits, so that both performance and execution integrity are guaranteed at the same time in a self-driving vehicle.

VI. CONCLUSION

In this article, we have conducted a comprehensive and systematic survey on the security threats, defenses, and future directions of AVs. First, we have targeted three

types of potential attacks against the existing AVs, focusing on security threats of sensors, in-vehicle systems, and in-vehicle protocols, respectively, and gave corresponding defense strategies. Second, we have further divided into the future of AVs, i.e., self-driving vehicles based on deep-learning algorithms, and elaborated the new security threats therein. Specifically, we have

focused on the security threats of the deep-learning model, including system errors, adversarial examples, model privacy, and hardware security. We have also presented potential practical defense strategies for all the mentioned new threats, aiming to provide a useful security guideline to boost the development of fully automated self-driving vehicles. ■

REFERENCES

- [1] C. Thorpe, M. Herbert, T. Kanade, and S. Shafter, "Toward autonomous driving: The CMU Navlab. II. Architecture and systems," *IEEE Expert*, vol. 6, no. 4, pp. 44–52, Aug. 1991.
- [2] T. Luettel, M. Himmelsbach, and H.-J. Wuensche, "Autonomous ground vehicles—Concepts and a path to the future," *Proc. IEEE*, vol. 100, Special Centennial Issue, pp. 1831–1839, May 2012.
- [3] (2018). *Autonomous Vehicle Sales to Surpass 33 Million Annually in 2040, Enabling New Autonomous Mobility in More Than 26 Percent of New Car Sales*, IHS Markit Says. [Online]. Available: <https://technology.ihs.com/599099/autonomous-vehicle-sales-to-surpass-33-million-annually-in-2040-enabling-new-autonomous-mobility-in-more-than-26-percent-of-new-car-sales-ihs-markit-says>
- [4] C. Yan, W. Xu, and J. Liu, "Can you trust autonomous vehicles: Contactless attacks against sensors of self-driving vehicle," in *Proc. DEFCON*, vol. 24, 2016.
- [5] J. V. Carroll, "Vulnerability assessment of the US transportation infrastructure that relies on the global positioning system," *J. Navigat.*, vol. 56, no. 2, pp. 185–193, 2003.
- [6] J. S. Warner and R. G. Johnston, "A simple demonstration that the global positioning system (GPS) is vulnerable to spoofing," *J. Secur. Admin.*, vol. 25, no. 2, pp. 19–27, 2002.
- [7] T. E. Humphreys, B. M. Ledvina, M. L. Psiaki, B. W. O'Hanlon, and P. M. Kintner, "Assessing the spoofing threat: Development of a portable GPS civilian spoofer," in *Proc. Radionavigat. Lab. Conf.*, 2008, pp. 2314–2325.
- [8] M. L. Psiaki and T. E. Humphreys, "GNSS spoofing and detection," *Proc. IEEE*, vol. 104, no. 6, pp. 1258–1270, Jun. 2016.
- [9] K. C. Zeng et al., "All your GPS are belong to us: Towards stealthy manipulation of road navigation systems," in *Proc. 27th USENIX Secur. Symp. (USENIX Secur.)*, 2018, pp. 1527–1544.
- [10] N. O. Tippenhauer, C. Pöpper, K. B. Rasmussen, and S. Capkun, "On the requirements for successful GPS spoofing attacks," in *Proc. 18th ACM Conf. Comput. Commun. Secur. (CCS)*, 2011, pp. 75–86.
- [11] T. Nighswander, B. Ledvina, J. Diamond, R. Brumley, and D. Brumley, "GPS software attacks," in *Proc. ACM Conf. Comput. Commun. Secur. (CCS)*, 2012, pp. 450–461.
- [12] A. J. Kerns, D. P. Shepard, J. A. Bhatti, and T. E. Humphreys, "Unmanned aircraft capture and control via GPS spoofing," *J. Field Robot.*, vol. 31, no. 4, pp. 617–636, 2014.
- [13] J. Bhatti and T. E. Humphreys, "Hostile control of ships via false GPS signals: Demonstration and detection," *J. Inst. Navigat.*, vol. 64, no. 1, pp. 51–66, 2017.
- [14] (2016). *LIDAR and Autonomous Technology*. [Online]. Available: <http://velodynelidar.com/newsroom/lidar-autonomous-technology/>
- [15] H. Shin, D. Kim, Y. Kwon, and Y. Kim, "Illusion and dazzle: Adversarial optical channel exploits against lidars for automotive applications," in *Proc. Int. Conf. Cryptograph. Hardw. Embedded Syst. (CHES)*. Cham, Switzerland: Springer, 2017, pp. 445–467.
- [16] J. Petit, B. Stottelaar, M. Feiri, and F. Kargl, "Remote attacks on automated vehicles sensors: Experiments on camera and LiDAR," in *Proc. Black Hat Eur.*, vol. 11, 2015, p. 2015.
- [17] M. L. Skolnik, *Radar Handbook*. New York, NY, USA: McGraw-Hill, 1990.
- [18] (2018). *LiDAR vs. RADAR*. [Online]. Available: <https://www.sensorsmag.com/components/lidar-vs-radar>
- [19] M. Zhou, Q. Wang, K. Ren, D. Koutsounikolas, L. Su, and Y. Chen, "Dolphin: Real-time hidden acoustic signal capture with smartphones," *IEEE Trans. Mobile Comput.*, vol. 18, no. 3, pp. 560–573, Mar. 2019.
- [20] M. Zhou, Q. Wang, T. Lei, Z. Wang, and K. Ren, "Enabling online robust barcode-based visible light communication with realtime feedback," *IEEE Trans. Wireless Commun.*, vol. 17, no. 12, pp. 8063–8076, Dec. 2018.
- [21] M. Zhou et al., "PatternListener: Cracking Android pattern lock using acoustic signals," in *Proc. 25th ACM Conf. Comput. Commun. Secur. (CCS)*, 2018, pp. 1775–1787.
- [22] W. Xu, C. Yan, W. Jia, X. Ji, and J. Liu, "Analyzing and enhancing the security of ultrasonic sensors for autonomous vehicles," *IEEE Internet Things J.*, vol. 5, no. 6, pp. 5015–5029, Dec. 2018.
- [23] J. S. Warner and R. G. Johnston, "GPS spoofing countermeasures," *Homeland Secur. J.*, vol. 25, no. 2, pp. 19–27, 2003.
- [24] K. D. Wesson, D. P. Shepard, J. A. Bhatti, and T. E. Humphreys, "An evaluation of the vestigial signal defense for civil GPS anti-spoofing," in *Proc. Radionavigat. Lab. Conf.*, 2011, pp. 1–11.
- [25] A. Konovalov, M. Cuntz, C. Haettich, and M. Meurer, "Autonomous spoofing detection and mitigation in a GNSS receiver with an adaptive antenna array," in *Proc. ION GNSS*, 2013, pp. 2937–2948.
- [26] P. Y. Montgomery, T. E. Humphreys, and B. M. Ledvina, "A multi-antenna defense: Receiver-autonomous GPS spoofing detection," *Inside GNSS*, vol. 4, no. 2, pp. 40–46, 2009.
- [27] M. L. Psiaki, B. W. O'Hanlon, S. P. Powell, J. A. Bhatti, K. D. Wesson, and T. E. Humphreys, "GNSS spoofing detection using two-antenna differential carrier phase," in *Proc. Radionavigat. Lab. Conf.*, 2014, pp. 2776–2800.
- [28] S. Daneshmand, A. Jafarinia-Jahromi, A. Broumandan, and G. Lachapelle, "A low-complexity GPS anti-spoofing method using a multi-antenna array," in *Proc. ION GNSS*, 2012, pp. 1233–1243.
- [29] M. L. Psiaki, S. P. Powell, and B. W. O'Hanlon, "GNSS spoofing detection using high-frequency antenna motion and carrier-phase data," in *Proc. ION GNSS+ Meeting*, 2013, pp. 2949–2991.
- [30] B. W. O'Hanlon, M. L. Psiaki, J. A. Bhatti, D. P. Shepard, and T. E. Humphreys, "Real-time GPS spoofing detection via correlation of encrypted signals," *Navigation*, vol. 60, no. 4, pp. 267–278, 2013.
- [31] A. J. Kerns, K. D. Wesson, and T. E. Humphreys, "A blueprint for civil GPS navigation message authentication," in *Proc. IEEE/ION Position, Location Navigat. Symp. (PLANS)*, May 2014, pp. 262–269.
- [32] L. Scott, "Anti-spoofing & authenticated signal architectures for civil navigation systems," in *Proc. 16th Int. Tech. Meeting Satell. Division Inst. Navigat. (ION GPS/GNSS)*, 2001, pp. 1543–1552.
- [33] C. Bahlmann, Y. Zhu, V. Ramesh, M. Pellkofer, and T. Koehler, "A system for traffic sign detection, tracking, and recognition using color, shape, and motion information," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2005, pp. 255–260.
- [34] H.-Y. Cheng, B.-S. Jeng, P.-T. Tseng, and K.-C. Fan, "Lane detection with moving vehicles in the traffic scenes," *IEEE Trans. Intell. Transp. Syst.*, vol. 7, no. 4, pp. 571–582, Dec. 2006.
- [35] C. Häne, T. Sattler, and M. Pollefeys, "Obstacle detection for self-driving cars using only monocular cameras and wheel odometry," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Sep./Oct. 2015, pp. 5101–5108.
- [36] S. Brands and D. Chaum, "Distance-bounding protocols," in *Proc. Workshop Theory Appl. Cryptograph. Techn.*, 1993, pp. 344–359.
- [37] K. B. Rasmussen and S. Capkun, "Realization of RF distance bounding," in *Proc. 19th USENIX Secur. Symp. (USENIX Secur.)*, 2010, pp. 389–402.
- [38] (1995). *The Basics of Microscopy*. [Online]. Available: <http://www.vanosta.be/microscopy.htm>
- [39] S. Bono, M. Green, A. Stubblefield, A. Juels, A. D. Rubin, and M. Szydlo, "Security analysis of a cryptographically-enabled RFID device," in *Proc. 14th USENIX Secur. Symp. (USENIX Secur.)*, 2005, pp. 1–15.
- [40] A. Francillon, B. Danev, and S. Capkun, "Relay attacks on passive keyless entry and start systems in modern cars," in *Proc. Netw. Distrib. Syst. Secur. Symp. (NDSS)*, 2011, pp. 1–16.
- [41] R. Verdult, F. D. Garcia, and J. Balasch, "Gone in 360 seconds: Hijacking with Hitag2," in *Proc. 21st USENIX Secur. Symp. (USENIX Secur.)*, 2012, pp. 237–252.
- [42] R. Verdult, F. D. Garcia, and B. Ege, "Dismantling megamos crypto: Wirelessly lockpicking a vehicle immobilizer," in *Proc. 22th USENIX Secur. Symp. (USENIX Secur.)*, 2013, pp. 703–718.
- [43] J. Takahashi and T. Fukunaga, "Implementation attacks on an immobilizer protocol stack," in *Proc. 11th Embedded Secur. Cars Conf. Eur. (ESCAR Eur.)*, 2013.
- [44] A. I. Alrabady and S. M. Mahmud, "Analysis of attacks against the security of keyless-entry systems for vehicles and suggestions for improved designs," *IEEE Trans. Veh. Technol.*, vol. 54, no. 1, pp. 41–50, Jan. 2005.
- [45] (2012). *Lock Jammers' Steal Cars in a Click*. [Online]. Available: <https://www.telegraph.co.uk/news/uknews/crime/9623150/Lock-jammers-steal-cars-in-a-click.html>
- [46] S. van de Beek, R. Vogt-Ardatjew, and F. Leferink, "Robustness of remote keyless entry systems to intentional electromagnetic interference," in *Proc. Int. Symp. Electromagn. Compat. (EMC)*, Sep. 2014, pp. 1242–1245.
- [47] W. A. Radasky, C. E. Baum, and M. W. Wik, "Introduction to the special issue on high-power electromagnetics (HPME) and intentional electromagnetic interference (IEMI)," *IEEE Trans. Electromagn. Compat.*, vol. 46, no. 3, pp. 314–321, Aug. 2004.
- [48] (2014). *Jam Intercept and Replay Attack Against Rolling Code KeyFob Entry Systems Using RTL-SDR*. [Online]. Available: <http://spencerwhyte.blogspot.ca/2014/03/delay-attack-jam-intercept-and-replay.html>
- [49] S. Kamkar, "Drive it like you hacked it: New attacks and tools to wirelessly steal cars," in *Proc. DEFCON*, vol. 23, 2015.
- [50] A. Bogdanov, "Attacks on the KeeLoq block cipher and authentication systems," in *Proc. 3rd Citeseer Conf. RFID Secur.*, 2007, pp. 929–944.
- [51] T. Eisenbarth, T. Kasper, A. Moradi, C. Paar, M. Salmisizadeh, and M. T. M. Shalmani, "On the

- power of power analysis in the real world: A complete break of the KeeLoq code hopping scheme," in *Proc. Annu. Int. Cryptol. Conf. (Crypto)*, 2008, pp. 203–220.
- [52] F. D. Garcia, D. Oswald, T. Kasper, and P. Pavlidis, "Lock it and still lose it—On the (in)security of automotive remote keyless entry systems," in *Proc. 25th USENIX Secur. Symp. (USENIX Secur.)*, 2016, pp. 929–944.
- [53] S. Tillich and M. Wójcik, "Security analysis of an open car immobilizer protocol stack," in *Proc. 4th Int. Conf. Trusted Syst. (INTRUST)*, 2012, pp. 83–94.
- [54] S. Mangard, E. Oswald, and T. Popp, *Power Analysis Attacks: Revealing the Secrets of Smart Cards*. New York, NY, USA: Springer, 2010.
- [55] M. Joye and M. Tunstall, Eds., *Fault Analysis in Cryptography* (Information Security and Cryptography). Berlin, Germany: Springer, 2012.
- [56] G. P. Hancke, K. E. Mayes, and K. Markantonakis, "Confidence in smart token proximity: Relay attacks revisited," *Comput. Secur.*, vol. 28, no. 7, pp. 615–627, 2009.
- [57] S. Drimer and S. J. Murdoch, "Keep your enemies close: Distance bounding against smartcard relay attacks," in *Proc. 16th USENIX Secur. Symp. (USENIX Secur.)*, vol. 312, 2007, pp. 87–102.
- [58] Y.-C. Hu, A. Perrig, and D. B. Johnson, "Wormhole attacks in wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 2, pp. 370–380, Feb. 2006.
- [59] N. Carlini et al., "Hidden voice commands," in *Proc. 25th USENIX Secur. Symp. (USENIX Secur.)*, 2016, pp. 513–530.
- [60] G. Zhang, C. Yan, X. Ji, T. Zhang, T. Zhang, and W. Xu, "DolphinAttack: Inaudible voice commands," in *Proc. ACM SIGSAC Conf. Comput. Commun. Secur. (CCS)*, 2017, pp. 103–117.
- [61] N. Roy, S. Shen, H. Hassanieh, and R. R. Choudhury, "Inaudible voice commands: The long-range attack and defense," in *Proc. 15th USENIX Symp. Netw. Syst. Design Implement. (NSDI)*, 2018, pp. 547–560.
- [62] N. Carlini and D. A. Wagner, "Audio adversarial examples: Targeted attacks on speech-to-text," in *Proc. IEEE Secur. Privacy Workshops*, May 2018, pp. 1–7.
- [63] *An Introduction to KeeLoq Code Hopping*, TB003, Microchip, DS91002A, Microchip Technol. Inc., Chandler, AZ, USA, 1996.
- [64] M. Zhou, Z. Qin, X. Lin, S. Hu, Q. Wang, and K. Ren, "Hidden voice commands: Attacks and defenses on the VCS of autonomous driving cars," *IEEE Wireless Commun.*, to be published, doi: 10.1109/MWC.2019.1800477.
- [65] (2011). *Lock it or Lose it*. [Online]. Available: <https://www.youtube.com/watch?v=Mmi2LRF7al8>
- [66] G. P. Hancke and M. G. Kuhn, "An RFID distance bounding protocol," in *Proc. 1st IEEE Int. Conf. Secur. Privacy Emerg. Areas Commun. Netw. (SECURECOMM)*, Sep. 2005, pp. 67–73.
- [67] C. H. Kim and G. Avoine, "RFID distance bounding protocol with mixed challenges to prevent relay attacks," in *Proc. Int. Conf. Cryptol. Netw. Secur. (CANS)*, 2009, pp. 119–133.
- [68] A. Moradi and T. Kasper, "A new remote keyless entry system resistant to power analysis attacks," in *Proc. 7th IEEE Int. Conf. Inf. Commun. Signal Process. (ICICSP)*, Dec. 2009, pp. 1–6.
- [69] X. Yuan et al., "CommanderSong: A systematic approach for practical adversarial voice recognition," in *Proc. 27th USENIX Secur. Symp. (USENIX Secur.)*, 2018, pp. 49–64.
- [70] S. Hu, X. Shang, Z. Qin, M. Li, Q. Wang, and C. Wang, "Adversarial examples for automatic speech recognition: Attacks and countermeasures," *IEEE Commun. Mag.*, vol. 57, no. 10, pp. 120–126, Oct. 2019, doi: 10.1109/MCOM.2019.1900006.
- [71] Q. Wang et al., "VoicePop: A pop noise based anti-spoofing system for voice authentication on smartphones," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, Apr./May 2019, pp. 2062–2070.
- [72] L. Wu, J. Yang, M. Zhou, Y. Chen, and Q. Wang, "LVID: A multimodal biometrics authentication system on smartphones," *IEEE Trans. Inf. Forensics Security*, to be published, doi: 10.1109/TIFS.2019.2944058.
- [73] X. Lin, X. Sun, P.-H. Ho, and X. Shen, "GSIS: A secure and privacy-preserving protocol for vehicular communications," *IEEE Trans. Veh. Technol.*, vol. 56, no. 6, pp. 3442–3456, Nov. 2007.
- [74] S. C. HPL, "Introduction to the controller area network (CAN)," *Appl. Rep. SLOA101*, 2002, pp. 1–17.
- [75] K. Koscher et al., "Experimental security analysis of a modern automobile," in *Proc. IEEE Symp. Secur. Privacy (S P)*, May 2010, pp. 447–462.
- [76] C. Miller and C. Valasek, "Adventures in automotive networks and control units," in *Proc. DEFCON*, vol. 21, Aug. 2013, pp. 260–264.
- [77] K.-T. Cho and K. G. Shin, "Error handling of in-vehicle networks makes them vulnerable," in *Proc. ACM SIGSAC Conf. Comput. Commun. Secur. (CCS)*, 2016, pp. 1044–1055.
- [78] S. Checkoway et al., "Comprehensive experimental analyses of automotive attack surfaces," in *Proc. 20th USENIX Secur. Symp. (USENIX Secur.)*, vol. 4, 2011, pp. 447–462.
- [79] C. Miller and C. Valasek, "Remote exploitation of an unaltered passenger vehicle," in *Proc. Black Hat USA*, 2015, p. 91.
- [80] S. Nie, L. Liu, and Y. Du, "Free-fall: Hacking Tesla from wireless to CAN bus," in *Proc. Briefing, Black Hat USA*, 2017, pp. 1–16.
- [81] J. M. Ernst and A. J. Michaels, "LIN bus security analysis," in *Proc. 44th Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Oct. 2018, pp. 2085–2090.
- [82] J. Takahashi et al., "Automotive attacks and countermeasures on LIN-bus," *J. Inf. Process.*, vol. 25, pp. 220–228, Jan. 2017.
- [83] D. K. Nilsson, U. E. Larsson, F. Picasso, and E. Jonsson, "A first simulation of attacks in the automotive network communications protocol flexray," in *Proc. Int. Workshop Comput. Intell. Secur. Inf. Syst. (CISIS)*, 2009, pp. 84–91.
- [84] M. Wolf, A. Weimerskirch, and C. Paar, "Security in automotive bus systems," in *Proc. 2nd Int. Conf. Embedded Secur. Cars (ESCAR)*, 2004, pp. 1–13.
- [85] J. H. Kim, S.-H. Seo, N. T. Hai, B. M. Cheon, Y. S. Lee, and J. W. Jeon, "Gateway framework for in-vehicle networks based on CAN, FlexRay, and Ethernet," *IEEE Trans. Veh. Technol.*, vol. 64, no. 10, pp. 4472–4486, Oct. 2015.
- [86] L. Yu, J. Deng, R. R. Brooks, and S. B. Yun, "Automobile ECU design to avoid data tampering," in *Proc. 10th ACM Annu. Cyber Inf. Secur. Res. Conf. (CISRC)*, 2015, Art. no. 10.
- [87] S. Woo, H. J. Jo, and D. H. Lee, "A practical wireless attack on the connected car and security protocol for in-vehicle CAN," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 2, pp. 993–1006, Apr. 2015.
- [88] D. K. Nilsson, U. E. Larsson, and E. Jonsson, "Efficient in-vehicle delayed data authentication based on compound message authentication codes," in *Proc. IEEE 68th Veh. Technol. Conf. (VTC)*, Sep. 2008, pp. 1–5.
- [89] C. Szilagyi and P. Koopman, "Low cost multicast authentication via validity voting in time-triggered embedded control networks," in *Proc. 5th ACM Workshop Embedded Syst. Secur. (WESS)*, 2010, Art. no. 10.
- [90] B. Groza, S. Murvay, A. van Herrewwege, and I. Verbauwhede, "LiRA-CAN: A lightweight broadcast authentication protocol for controller area networks," in *Proc. Int. Conf. Cryptol. Netw. Secur. (CANS)*, 2012, pp. 185–200.
- [91] Y. Weisglass, "Practical attacks on CAN message authentication," in *Proc. 4th Int. Conf. Embedded Secur. Cars (ESCAR Asia)*, 2017.
- [92] T. Matsumoto, M. Hata, M. Tanabe, K. Yoshioka, and K. Oishi, "A method of preventing unauthorized data transmission in controller area network," in *Proc. IEEE 75th Veh. Technol. Conf. (VTC)*, May 2012, pp. 1–5.
- [93] R. Kurachi, Y. Matsubara, H. Takada, N. Adachi, Y. Miyashita, and S. Horiata, "CaCAN-centralized authentication system in CAN (controller area network)," in *Proc. 12th Int. Conf. Embedded Secur. Cars (ESCAR)*, 2014.
- [94] Y. Ujiiie et al., "A method for disabling malicious CAN messages by using a CMI-ECU," *SAE Tech. Paper 2016-01-0068*, 2016.
- [95] D. D. Yao, X. Shu, L. Cheng, and S. J. Stolfo, *Anomaly Detection as a Service: Challenges, Advances, and Opportunities* (Synthesis Lectures on Information Security, Privacy, and Trust). San Rafael, CA, USA: Morgan & Claypool, 2017.
- [96] L. Cheng, K. Tian, and D. D. Yao, "Orpheus: Enforcing cyber-physical execution semantics to defend against data-oriented attacks," in *Proc. 33rd Annu. Comput. Secur. Appl. Conf.*, 2017, pp. 315–326.
- [97] L. Cheng, K. Tian, D. Yao, L. Sha, and R. A. Beyah, "Checking is believing: Event-aware program anomaly detection in cyber-physical systems," *IEEE Trans. Dependable Secure Comput.*, to be published.
- [98] U. E. Larsson, D. K. Nilsson, and E. Jonsson, "An approach to specification-based attack detection for in-vehicle networks," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2008, pp. 220–225.
- [99] M. Muter, A. Groll, and F. C. Freiling, "A structured approach to anomaly detection for in-vehicle networks," in *Proc. 6th Int. Conf. Inf. Assurance Secur. (IAS)*, 2010, pp. 92–98.
- [100] A. Taylor, N. Japkowicz, and S. Leblanc, "Frequency-based anomaly detection for the automotive CAN bus," in *Proc. IEEE Intell. Vehicles Symp. World Congr. Ind. Control Syst. Secur. (WCICSS)*, Dec. 2015, pp. 45–49.
- [101] P.-S. Murvay and B. Groza, "Source identification using signal characteristics in controller area networks," *IEEE Signal Process. Lett.*, vol. 21, no. 4, pp. 395–399, Apr. 2014.
- [102] W. Choi, H. J. Jo, S. Woo, J. Y. Chun, J. Park, and D. H. Lee, "Identifying ecus using inimitable characteristics of signals in controller area networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 6, pp. 4757–4770, Jun. 2018.
- [103] (2016). *Taxonomy and Definitions for Terms Related to on-Road Motor Vehicle Automated Driving Systems* [Online]. Available: https://www.sae.org/standards/content/j3016_201401/
- [104] A. Balakrishnan et al., "Specifying and evaluating quality metrics for vision-based perception systems," in *Proc. Design, Autom. Test Eur. Conf. Exhib. (DATE)*, 2019, pp. 1433–1438.
- [105] (2019). *Uber Cleared Over Arizona Pedestrian's Self-Driving Car Death*. [Online]. Available: <http://fortune.com/2019/03/06/uber-cleared-arizona-self-driving-death/>
- [106] K. Eykholt et al., "Robust physical-world attacks on deep learning models," 2017, *arXiv:1707.08945*. [Online]. Available: <https://arxiv.org/abs/1707.08945>
- [107] A. Chernikova, A. Oprea, C. Nita-Rotaru, and B. Kim, "Are self-driving cars secure? Evasion attacks against deep neural networks for steering angle prediction," 2019, *arXiv:1904.07370*. [Online]. Available: <https://arxiv.org/abs/1904.07370>
- [108] C. Sitawarin, A. N. Bhagoji, A. Mosenia, M. Chiang, and P. Mittal, "DARTS: Deceiving autonomous cars with toxic signs," 2018, *arXiv:1802.06430*. [Online]. Available: <https://arxiv.org/abs/1802.06430>
- [109] A. N. Bhagoji, W. He, B. Li, and D. Song, "Practical black-box attacks on deep neural networks using efficient query mechanisms," in *Proc. Eur. Conf. Comput. Vis. Cham, Switzerland: Springer*, 2018, pp. 158–174.
- [110] C. Xiao, B. Li, J.-Y. Zhu, W. He, M. Liu, and D. Song, "Generating adversarial examples with adversarial networks," 2018, *arXiv:1801.02610*. [Online]. Available: <https://arxiv.org/abs/1801.02610>
- [111] Q. Wang, Y. Zhang, X. Lu, Z. Wang, Z. Qin, and K. Ren, "Real-time and spatio-temporal crowd-sourced social network data publishing with differential privacy," *IEEE Trans. Dependable Secure Comput.*, vol. 15, no. 4, pp. 591–606, Jul./Aug. 2018.
- [112] N. Carlini, C. Liu, J. Kos, Ú. Erlingsson, and

- D. Song, "The secret sharer: Measuring unintended neural network memorization & extracting secrets," 2018, *arXiv:1802.08232*. [Online]. Available: <https://arxiv.org/abs/1802.08232>
- [113] S.-C. Lin et al., "The architectural implications of autonomous driving: Constraints and acceleration," *ACM SIGPLAN Notices*, vol. 53, no. 2, pp. 751–766, 2018.
- [114] A. C. Berg and J. Malik, "Geometric blur for template matching," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. (CVPR)*, vol. 1, Dec. 2001, p. 1.
- [115] X. Chen, C. Liu, and D. Song, "Tree-to-tree neural networks for program translation," in *Proc. Adv. Neural Inf. Process. Syst.*, 2018, pp. 2547–2557.
- [116] (2017). *Federated Learning: Collaborative Machine Learning Without Centralized Training Data*. [Online]. Available: <https://ai.googleblog.com/2017/04/federated-learning-collaborative>
- [117] I. Dinur and K. Nissim, "Revealing information while preserving privacy," in *Proc. 22nd ACM SIGACT-SIGMOD-SIGART Symp. Princ. Database Syst. (PODS)*, 2003, pp. 202–210.
- [118] C. Dwork, "Differential privacy: A survey of results," in *Proc. Theory Appl. Models Comput. (TAMC)*, 2008, pp. 1–19.
- [119] L. Zhao, Q. Wang, Q. Zou, Y. Zhang, and Y. Chen, "Privacy-preserving collaborative deep learning with unreliable participants," *IEEE Trans. Inf. Forensics Security*, to be published, doi: [10.1109/TIFS.2019.2939713](https://doi.org/10.1109/TIFS.2019.2939713).
- [120] J. S. Jang, S. Kong, M. Kim, D. Kim, and B. B. Kang, "SeCReT: Secure channel between rich execution environment and trusted execution environment," in *Proc. NDSS*, 2015, pp. 1–15.
- [121] V. Costan and S. Devadas, "Intel SGX explained," *IACR Cryptol. ePrint Arch.*, vol. 2016, no. 86, pp. 1–118, 2016.
- [122] S. Mofrad, F. Zhang, S. Lu, and W. Shi, "A comparison study of intel SGX and AMD memory encryption technology," in *Proc. ACM 7th Int. Workshop Hardw. Archit. Support Secur. Privacy*, 2018, Art. no. 9.

ABOUT THE AUTHORS

Kui Ren (Fellow, IEEE) received the Ph.D. degree from the Worcester Polytechnic Institute, Worcester, MA, USA.

He is currently a Professor of computer science and technology and the Director of the Institute of Cyberspace Research, Zhejiang University, Hangzhou, Zhejiang, China. His current research interests include cloud and outsourcing security, wireless and wearable system security, and artificial intelligence security.

Dr. Ren is also a Distinguished Scientist of the ACM. He was a recipient of the IEEE CISTC Technical Recognition Award 2017 and the NSF CAREER Award in 2011.



Qian Wang (Senior Member, IEEE) received the Ph.D. degree from the Illinois Institute of Technology, Chicago, IL, USA.

He is currently a Professor with the School of Cyber Science and Engineering, Wuhan University, Wuhan, China. His current research interests include AI security, data storage, search and computation outsourcing security and privacy, wireless systems security, big data security and privacy, and applied cryptography.

Dr. Wang is also a member of the ACM. He received the National Science Fund for Excellent Young Scholars of China in 2018. He is also an Expert under National 1000 Young Talents Program of China. He was a recipient of the 2016 IEEE Asia-Pacific Outstanding Young Researcher Award and the 2018 IEEE TCSC Award for Excellence in Scalable Computing (Early Career Researcher). He was a co-recipient of several Best Paper and Best Student Paper Awards from the IEEE International Conference on Network Protocols (ICNP) 2011, the International conference on Web-Age Information Management (WAIM) 2014, the IEEE International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom) 2016, the IEEE International Conference on Distributed Computing Systems (ICDCS) 2017, and so on. He also serves as an Associate Editor for the IEEE TRANSACTIONS ON DEPENDABLE AND SECURE COMPUTING (TDSC) and the IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY (TIFS).



Cong Wang (Senior Member, IEEE) received the Ph.D. degree from the Illinois Institute of Technology, Chicago, IL, USA.

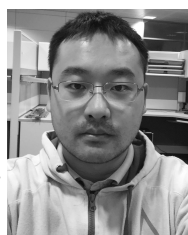
He is currently an Associate Professor with the Department of Computer Science, City University of Hong Kong. His current research interests include data security, network security, privacy-enhancing technologies, blockchain, and decentralized applications.



Dr. Wang is also a member of the ACM. He is one of the Founding Members of the Young Academy of Sciences of Hong Kong. He received the President's Award from the City University of Hong Kong in 2016, the Outstanding Supervisor Award in 2017, and the Outstanding Research Award in 2019. He was a co-recipient of the Best Student Paper Award of the IEEE International Conference on Distributed Computing Systems (ICDCS) 2017 and the Best Paper Award of the International Conference on Communications and Networking in China (CHINACOM) 2009, the International Conference on Mobile Ad-hoc and Sensor Networks (MSN) 2015, and the IEEE International Conference on Parallel and Distributed Systems (ICPADS) 2018. He has been serving as the TPC Co-Chair for a number of IEEE conferences/workshops. His research has been supported by multiple government research fund agencies, including the National Natural Science Foundation of China, the Hong Kong Research Grants Council, and the Hong Kong Innovation and Technology Commission. He has been serving as an Associate Editor for the IEEE TRANSACTIONS ON DEPENDABLE AND SECURE COMPUTING (TDSC), the IEEE INTERNET OF THINGS JOURNAL (IoT-J), and the IEEE NETWORKING LETTERS.

Zhan Qin (Member, IEEE) received the Ph.D. degree from the Computer Science and Engineering Department, The State University of New York at Buffalo, Buffalo, NY, USA, in 2017.

He was an Assistant Professor with the Department of Electrical and Computer Engineering, The University of Texas at San Antonio, San Antonio, TX, USA. He is currently a ZJU100 Young Professor with the College of Computer Science and Technology and the Institute of Cyberspace Research (ICSR), Zhejiang University, Hangzhou, China. His current research interests include data security and privacy, secure computation outsourcing, artificial intelligence security, and cyber-physical security in the context of the Internet of Things. His works explore and develop novel security-sensitive algorithms and protocols for computation and communication on the general context of cloud and Internet devices.



Xiaodong Lin (Fellow, IEEE) received the Ph.D. degree in information engineering from the Beijing University of Posts and Telecommunications, Beijing, China, and the Ph.D. degree in electrical and computer engineering from the University of Waterloo, Waterloo, ON, Canada.

He is currently an Associate Professor with the School of Computer Science, University of Guelph, Guelph, ON, Canada. His current research interests include computer and network security, privacy protection, applied cryptography, computer forensics, and software security.

Dr. Lin received the Outstanding Achievement Award in Graduate Studies for his Ph.D. degree from the University of Waterloo.

