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Cybersecurity

REVIEW

Hierarchical Security Survey of Voice Control Systems: Vulnerabilities, Countermeasures, and Future Horizons

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Abstract — The widespread adoption of voice control systems (VCSs) in smart devices and their growing integration into daily life highlight the urgent need to address their security challenges. Recent studies have revealed a range of vulnerabilities in VCSs, which threaten user privacy and safety. Despite these findings, there remains a notable absence of a comprehensive and systematic review that thoroughly examines these vulnerabilities and the corresponding defense strategies. This gap hinders VCS designers from fully understanding and addressing the security risks inherent in these systems. To bridge this gap, our research introduces a hierarchical model for VCS, providing a structured and innovative framework for organizing and analyzing existing literature. We categorize attacks based on their underlying technical principles and conduct an in-depth analysis of various aspects, such as attack methodologies, targets, vectors, and behaviors. Furthermore, we synthesize and critically evaluate current defense mechanisms, offering practical recommendations to strengthen VCS security. Analyzing VCS security from a hierarchical perspective, this work provides designers with the tools to effectively identify and mitigate potential threats while establishing a foundation for future research and advancements in VCS security.

Keywords — Speaker recognition, Voice control systems, Replay attack, Jamming attack, Voice-synthesis attack.

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I. Introduction

Voice control systems (VCSs) have emerged as a cornerstone of modern smart technologies, revolutionizing user-interaction paradigms across diverse applications, ranging from mobile devices to sophisticated smart home ecosystems. The rapid evolution of VCS has driven their widespread adoption, with the market projected to reach $15.6 billion by 2025. This remarkable expansion is fueled by the versatile capabilities of VCS, enabling users to seamlessly manage smart home environments, conduct online transactions, and access a wide range of digital services through intuitive voice commands. However, this rapid proliferation has simultaneously unveiled a complex array of security challenges, particularly with regard to data privacy and the

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increasing sophistication of cyberattacks targeting VCS infrastructures.

The complex architecture of VCS, with both software and hardware components, inherently hides a spectrum of security vulnerabilities. These vulnerabilities serve as potential avenues for malicious exploitation, posing serious challenges for VCS developers tasked with preemptively identifying and mitigating these multifaceted threats. For example, adversaries have demonstrated the ability to exploit hardware vulnerabilities in microphones to inject unauthorized commands into VCSs employing unconventional methods such as laser [1], [2]. Furthermore, the advent of adversarial machine learning techniques has enabled attackers to engineer audio commands that are imperceptible to human ears yet are interpreted as malicious instructions by VCS algorithms. In the realm of third-party VCS services, the integration of malicious applications that can be inadvertently activated by unsuspecting users further compounds security risks [3], [4]. Despite the diversity and complexity of these threats, most defense mechanisms often adopt a myopic focus, addressing isolated attack vectors without considering the holistic implications of vulnerabilities across the entire VCS. This fragmented approach not only limits the effectiveness of existing countermeasures but also prevents a comprehensive understanding of the interconnected risks and attack methodologies that threaten VCS infrastructures. Consequently, there is a pressing imperative for a systematic and integrative analysis that not only analyzes contemporary attack strategies but also critically evaluates the robustness and limitations of current defense frameworks, thereby paving the way for more resilient and adaptive security solutions in the VCS domain.

Related survey and limitations Our survey distinguishes itself from prior research by categorizing the structure of VCS into distinct layers: the physical layer, the data layer, the model layer, and the service layer. This approach enables a comprehensive examination of security risks and defense mechanisms, considering each layer's specific integration perspective. Table 1 ([4]–[10]) provides a comparative summary of our work in relation to similar studies. For example, Zhang *et al.* [4] focused specifically on security threats from malicious services within VCS. Bai *et al.* [6] explored acoustic technologies and their applications in domestic and industrial settings. Abdullah *et al.* [7] and Chen *et al.* [8] provided an in-depth analysis of the risks associated with automatic speech recognition (ASR) and speaker verification (SV) systems, integral components of VCS. Zhang *et al.* [9] surveyed adversarial attacks against ASRs in detail. Gurowiec *et al.* [10] provided a detailed study on attacks and defense schemes in speech emotion recognition systems. These studies, while insightful, often focus on specific layers or subsets of layers within VCS, possibly overlooking the full view of security threats. For example, Zhang *et al.* [4] and Bai *et al.* [6] did not comprehensively address vulnerabilities in the service layer. Similarly, studies in [7]–[9] primarily analyze the model layer, neglecting other critical layers. In contrast, our survey aims to bridge these gaps by providing an all-encompassing analysis of VCS security across all layers. Although the

Table 1 A comparison of existing survey work in the smart voice control systems

Article	Year	Major contribution	Scope									
			Attack					Defense				
			SVS	NLPS	HS	SWSS	MDS	SVS	NLPS	HS	SWSS	MDS
[4]	2019	A comprehensive study about third party skills with threats in VA and how to avoid them	✘	✘	✘	✔	✔	✘	✘	✘	✔	✔
[5]	2020	A thorough survey over the security and privacy of smart home personal assistants	✔	✔	✔	✔	✘	✔	✔	✔	✔	✘
[6]	2020	A comprehensive survey on acoustic-based technologies and applications in life and industry	✔	✘	✔	✘	✔	✘	✘	✘	✘	✔
[7]	2021	A detailed study about security threats and defense schemes in ASR and SV	✔	✘	✘	✘	✔	✔	✘	✘	✘	✔
[8]	2022	A modularized and comprehensive survey about ASR security and comparison between ASR and image recognition system (IRS) security	✘	✔	✘	✘	✔	✘	✔	✘	✘	✔
[9]	2022	A detailed investigation of adversarial attacks against ASR	✘	✘	✘	✘	✔	✘	✘	✘	✘	✔
[10]	2024	A detailed study about attacks and defense schemes in speech emotion recognition systems	✔	✔	✔	✔	✘	✔	✔	✔	✔	✘
Ours	2025	A comprehensive overview of the challenges faced by VCS and its future direction	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔

Note: SVS: speaker verification security. NLPS: natural language processing security. HS: hardware security. SWSS: skill web service security. MDS: mobile device security.

work in [5] presents a comprehensive overview of VCS attacks, it mainly focuses on smart home applications, omitting extensive discussion on mobile device integration. The work in [11] offers an exhaustive review of attacks and countermeasures in voice assistants (VAs), but lacks a structured view of VCS.

Vision and scope In addition to current surveys lacking a comprehensive perspective on examining VCS security issues, researchers also urgently need to address the following questions:

- VCS systems are vulnerable to a variety of attacks, such as transduction attacks, voice synthesis attacks, and adversarial attacks. This susceptibility stems from two main factors: the advancement of technology providing attackers with more sophisticated tools and algorithms, and the inherent complexity of VCS as a system comprising multiple hardware and software components, each with unique security vulnerabilities. Understanding how these attacks operate and identifying the specific vulnerabilities of VCS components are crucial for designers.
- Beyond understanding attack mechanisms, it is vital that VCS designers are aware of effective defense solutions. Current defense strategies, such as adversarial training, are often tailored to specific attack types [12]–[18], posing a challenge in selecting appropriate defense combinations to robustly enhance the VCS's ability to withstand a wide range of attacks.
- The diverse nature of VCS, which encompasses both ASR and SV, often leads to the study of these components in isolation [7], [8]. However, many VCS systems incorporate both ASR and SV functionalities, and attacks against these systems often exhibit overlapping characteristics. Designers must therefore jointly consider the vulnerabilities of both ASR and SV when developing VCS.

In our paper, we conduct a comprehensive and systematic study of VCS security. To thoroughly discuss the various attacks facing VCS, we categorize these attacks based on the hierarchical model of VCS, which includes the physical layer, the data layer, the model layer, and the service layer, and then analyze and assess the corresponding defense schemes, tailored to each type of attack within these layers as shown in Figure 1. For each attack, we conduct a multidimensional evaluation, considering aspects such as attack methods, targets, vectors, and performance impact, and discuss potential directions for future research. In addition, we of-

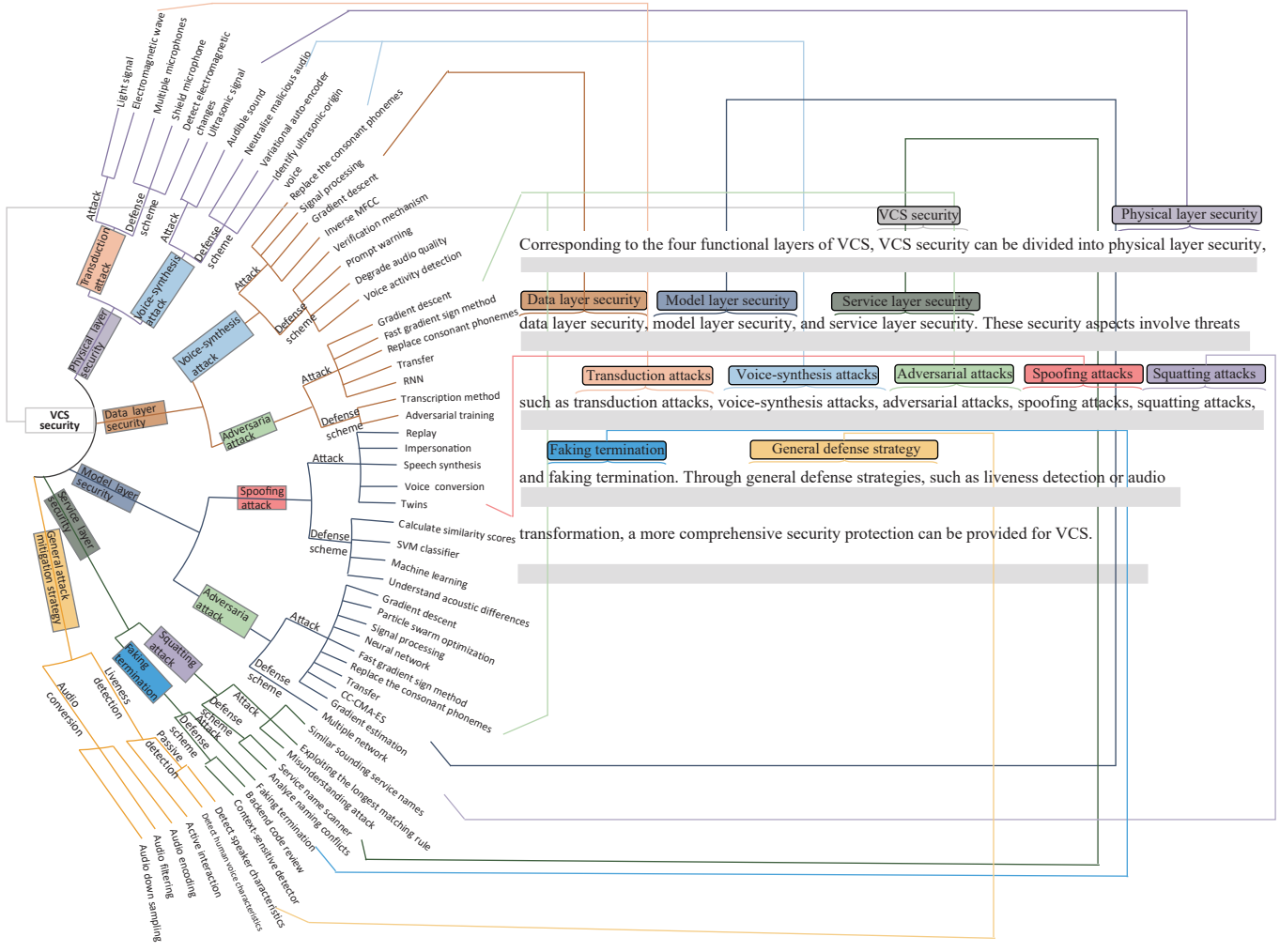

Figure 1 An illustrative overview of VCS security.

fer practical combinations of defense schemes, providing valuable insights for VCS researchers to effectively counter diverse attacks. An illustrative organizational structure for our survey article is presented in Figure 2.

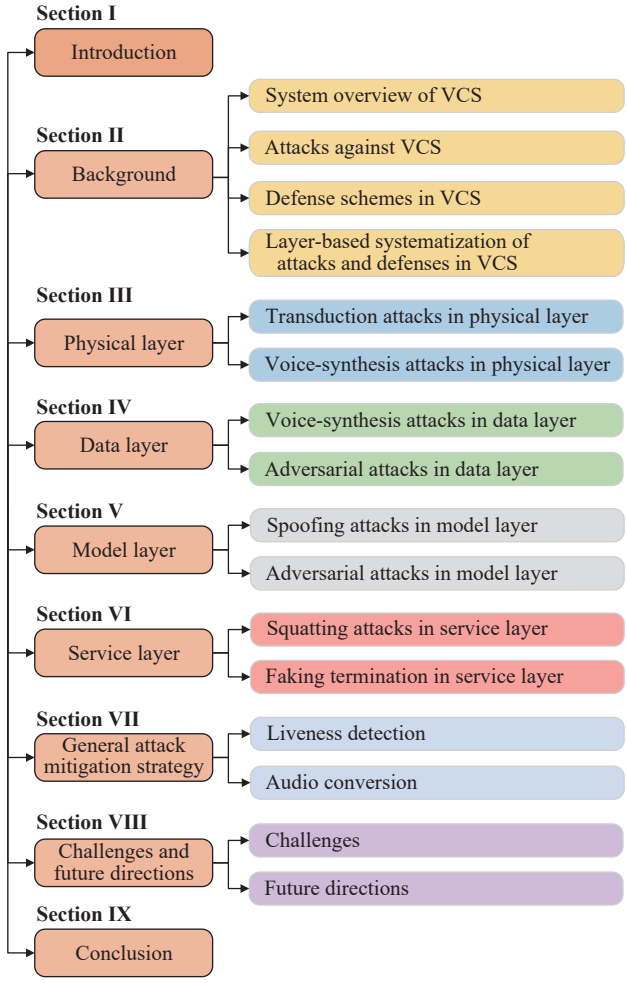

Figure 2 An illustrative overview of structure of our survey.

Our work distinguishes itself from existing surveys in several comprehensive aspects: i) We provide extensive coverage of a broad range of attack methods applicable to each layer within the hierarchical model of VCS. This approach offers a detailed understanding of the potential vulnerabilities at different levels of the system. ii) Our overview is expanded to include various devices that incorporate VCS, where we detail the unique security risks associated with each device type. This broadens the scope of our survey to encompass a wider array of real-world applications. iii) We present a detailed introduction to defense schemes corresponding to these attack methods, thereby enabling readers to not only understand these strategies but also to implement them in practical scenarios. This integrated approach to both attack and defense perspectives provides a well-rounded view of VCS security.

Contributions We summarize our contribution as follows:

- Our unique approach to examining VCS's security involves dividing VCS into four distinct layers: the physical layer, data layer, model layer, and service layer. This hierarchical model allows for a systematic and detailed analysis of both attacks and defense schemes at each layer, providing VCS researchers with a comprehensive framework to understand and evaluate associated risks accurately.
- Using our proposed hierarchical model, we have systematically integrated and assessed potential attacks on each VCS layer. By employing various metrics such as attack complexity and potential impact, we offer a feasibility analysis that enables users to accurately gauge the security threats posed to VCS by these attacks.
- We have developed and evaluated defense strategies tailored to each layer of VCS, considering practical effectiveness and usability from multiple dimensions. In addition, we introduce a generalized attack mitigation strategy to help designers construct a more robust and comprehensive defense system for VCS.
- Through an extensive analysis of existing literature, we provide targeted recommendations to enhance current security research and directions for future development in the field, addressing gaps and emerging trends in VCS security research.

II. Background

In this section, we brief the system overview of VCS, and then systematically describe layer-based attacks and defensive schemes.

1. System overview of VCS

As Siri achieved significant success on iPhones, VCS have seen widespread integration into daily life. Nowadays, smart devices including smartphones, smart home devices, and smart vehicles, are equipped with voice assistants. VCS enable users to perform various tasks such as unlocking devices, setting alarms, and opening doors, thereby enhancing interaction with smart technology. Popular VCSs including Google Home, Amazon Echo, and Apple HomePod, have expanded their capabilities through third-party services, providing features like voice translation and audio transcription.

With the rapid development and increasing prevalence of VCS, security concerns are likewise growing. To thoroughly analyze and effectively organize the potential risks and defensive strategies for voice assistants, we categorize the VCS into four functional layers: physical layer, data layer, model layer, and service layer. This layered approach allows for a detailed study of how a voice control system processes voice commands and provides services to users, as illustrated in Figure 3.

1) Physical layer

Transmission channels Acoustic signals, when transmitted over-the-air in VCS, are subject to various environmental influences that can degrade their quality [19]. The signal intensity diminishes with distance, which constrains the effective operational range be-

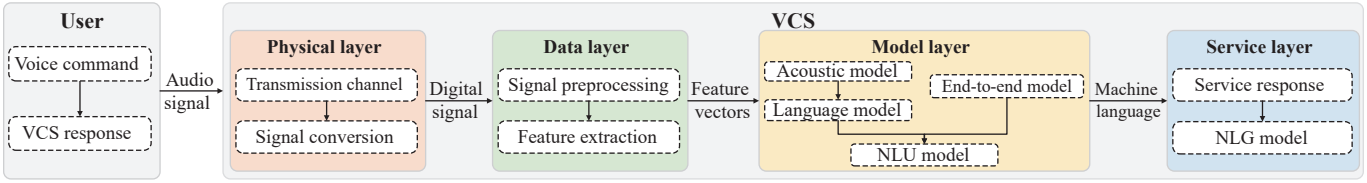

Figure 3 A hierarchical workflow diagram of VCS. After a user issues a voice command to the VCS, the user will receive a response from the VCS. Based on the response, the user can choose to issue another relevant command to the VCS.

tween the source and the target device. Furthermore, background noise and multipath effects caused by signal reflection result in the reception of mixed signals, complicating the interpretation of the original acoustic input. Like the channel vulnerability in WiFi sensing [20]–[24], this vulnerability in the transmission channel is particularly concerning in security contexts, where attackers could exploit these transmission challenges by deploying malicious audio. Such attacks might aim to compromise the VCS by leveraging signal interference, necessitating countermeasures. Attackers, aware of these transmission challenges, might enhance the robustness of their malicious audio or resort to generating electronic signals that mimic acoustic ones, to increase the likelihood of successful system penetration.

Acoustic signal conversion Acoustic signals must first be converted to digital signals for the VCS employing two critical stages. In the first stage, the system employs sensors, typically microphones, to transform acoustic signals into electrical signals. Among microphones, electrodynamics and capacitive types are widely used, with the latter being more prevalent in modern devices due to their sensitivity and reliability. Capacitive microphones operate by detecting changes in capacitance caused by the vibration of moving plates in response to sound waves, thus converting acoustic signals into electrical ones [25].

The second stage involves an analog-to-digital converter (ADC), which digitizes the electrical signals. The ADC employs a sample and holds circuit to capture and stabilize the signal value, followed by a quantizer that processes these samples, converting them into binary numbers representing the digital signal. This conversion is pivotal for effective VCS processing, but each stage also presents potential security vulnerabilities, such as susceptibility to signal manipulation or interference, that must be carefully managed to ensure system integrity.

2) Data layer

Signal preprocessing Signal preprocessing is vital in VCS, as it involves processing raw speech signals to extract clean speech for analysis. Band-pass filtering is a commonly used technique for VCS to isolate speech signals within the 300–3400 kHz frequency band. For devices with multiple microphones, techniques such as multichannel acoustic echo cancellation, reverberation control, and source separation, are essential for multichannel speech capture. These typical techniques ensure high-quality signal capture, crucial for accurate speech recognition. Recently, the development of the deep learning offers improved novel methods for noise mitigation and signal clarity [26], which is critical for robust VCS functioning, particularly in complex acoustic environments.

Acoustic feature extraction This module aims to extract distinctive features from speech signals, accounting for variations in speaker characteristics, environmental noise, and transmission channels. The process begins with segmenting the processed audio into frames using a sliding window technique, followed by feature extraction. Common algorithms for feature extraction include short-time Fourier transform (STFT), linear predictive coding (LPC) [27], Mel frequency cepstral coefficients (MFCC) [28], and perceptual linear prediction (PLP) [29]. Each algorithm plays a unique role in enhancing the robustness of VCS by efficiently capturing and representing different acoustic properties of speech.

3) Model layer

Acoustic model After the feature extraction in the data layer, the acoustic model establishes a statistical relationship between these features and acoustic units like phonemes using machine learning algorithms. Traditional models commonly use Gaussian mixture models (GMM) and hidden Markov models (HMM), while contemporary models increasingly employ neural networks such as convolutional neural networks (CNN) and recurrent neural networks (RNN) [30], enhancing the accuracy and efficiency of phoneme conversion.

Language model The language model predicts the likelihood of word sequences forming coherent sentences and distinguish homophones based on context. This model is pivotal in controlling VCS output using common words and grammatical rules. Models are generally divided into statistical models (e.g., N-gram, HMM) and neural network-based models, with the latter becoming increasingly prevalent in modern VCS.

Phonetic dictionary This component links the acoustic and language models by mapping words to phonemes, essential for decoding the user's intent in VCS. The phonetic dictionary facilitates the establishment of relationships between the models' units, thereby aiding in effective system decoding.

End-to-end model To streamline VCS, end-to-end models have been developed. These models directly convert acoustic features into word sequences, integrating the functions of both acoustic and language models. This simplification reduces potential attack vectors, en-

hancing system security. Examples include connectionist temporal classification (CTC) [31], Transducer [32], and Attention models [33].

Natural language processing (NLU) NLU model enables machines to understand and act upon natural language inputs. Its development has evolved from rule-based to statistical models, and now to neural network-based models like Word2vec [34] and BERT [35], reflecting the industry's shift towards more sophisticated, context-aware processing.

Speaker verification (SV) SV focuses on identifying the legal speaker rather than interpreting speech content. And it is also different from speaker identification (SI), with the latter confirming a speaker's identity. In the model layer, speaker verification differs from standard VCS in that it determines the likelihood that a speaker is who it claims to be, thus requiring specialized discussion regarding its security implications.

4) Service layer

After interpreting the user's intent in the model layer, the VCS responds in the service layer. Utilizing natural language generation (NLG), the system conveys the required information in text or audibly through text-to-speech (TTS) technology [36]. Technological advancements have expanded VCS capabilities to include third-party services, enabling more complex functionalities. However, this expansion introduces new security challenges, such as increased exposure to data breaches and exploitation of service vulnerabilities, necessitating robust security measures.

2. Attacks against VCS

As shown in Figure 4, current researches highlight the vulnerability of VCS to a range of attacks, stemming from its complex architecture which presents potential vulnerabilities at each layer. To equip system designers with a comprehensive understanding of these threats, this section delves into the nature of attacks against VCS, examining them from the perspectives of threat models, attack metrics, and attack objectives. We will explore how threat models help identify potential security weaknesses, discuss attack metrics to assess the impact and severity of attacks, and analyze the typical goals of attackers targeting VCS.

1) Threat model

We consider attack scenarios under these assumptions:

i) Attackers may have prior knowledge of the target VCS, including its brand and model. For common VCS, attackers might possess the same device model.

ii) The VCS operates on a trusted platform with

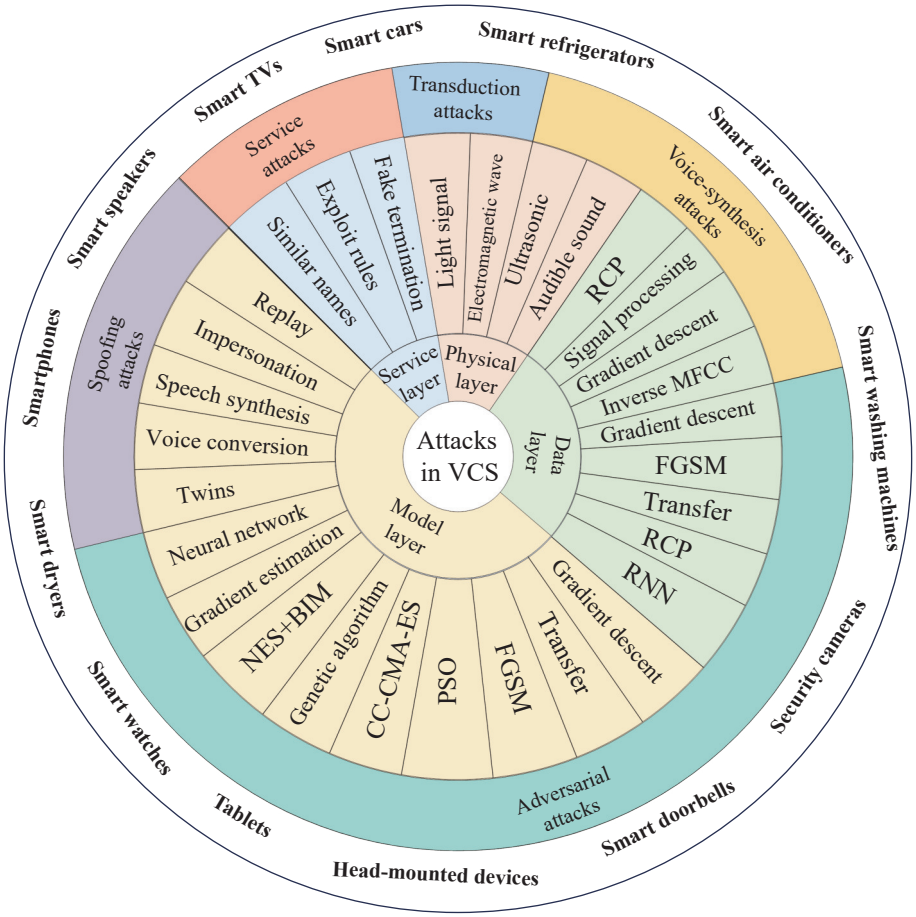

Figure 4 Attacks in the different layers of VCS. PSO: particle swarm optimization. ATN: adversarial transformation network. NES: natural evolution strategy. BIM: basic iterative method. CC-CMA-ES: cooperative-coevolution covariance-matrix-adaptation evolution-strategy. FGSM: fast gradient sign method. GN: generative network. GCA: convolutional auto-encoder. RCP: replacing the consonant phonemes.

encrypted communication, preventing attacks via the operating system, hardware, or communication interception.

iii) Attackers' knowledge varies: a) White/Grey-box: Full or partial model knowledge, applicable to open-source VCS. b) Black-box: No model knowledge, typical in commercial VCS.

2) Attack metrics

Based on the threat model, we assess VCS attacks as follows:

Attack method The method determines the targeted VCS layer. Some methods exploit non-audio signals to attack the physical layer, while others use audio-based methods to deceive the model layer.

Attack target Targets can vary from specific models (requiring detailed knowledge) to general hardware vulnerabilities that affect multiple VCS models [37].

Attack vector The vector refers to the carrier of the attack (e.g., the air, the power line, the solid surface) and must be robust against environmental factors and signal degradation.

Performance The effectiveness of an attack is measured by its success rate and the maximum effective distance, indicating its practicality in real scenarios.

3) Attack goal

Attackers primarily aim to disrupt VCS operations and cause command execution to be executed incorrectly. Untargeted attacks may cause incorrect audio decoding, while targeted attacks seek to execute specific malicious commands. Security impacts include unauthorized control of smart devices (e.g., unlocking doors), while privacy concerns involve eavesdropping or accessing personal information via malicious services.

3. Defense schemes in VCS

The range of defense strategies for VCS is relatively narrow compared to the diversity of attack methods. Current defenses primarily fall into two categories: i) Layer-specific solutions, such as adversarial training, which fortify particular layers like the model layer against specific types of attacks, yet they might not be effective against threats targeting other layers. This category also includes specialized encryption for communication security and hardware-focused protections. ii) Holistic strategies, like liveness detection, are designed to protect the entire VCS by verifying the authenticity of voice inputs, thereby securing all layers from a range of potential attacks. The VCS security often depends on the integration of both layer-specific and holistic defenses to fully address the multifaceted nature of potential threats.

4. Layer-based systematization of attacks and defenses in VCS

The approach for classifying attacks on VCS typically revolves around either human perception or specific VCS components. However, this method can inadvertently group distinct attack methodologies under the same category, despite their differing technical principles. For instance, both DolphinAttack [38] and hidden voice command [39] are categorized as voice-synthesis attacks. Nonetheless, they fundamentally differ in their mechanisms. DolphinAttack exploits microphone hardware vulnerabilities, while hidden voice command targets the data preprocessing algorithms.

Although the component-based classification method provides a systematic approach to categorize attacks, it often leads to an isolated analysis of SV and ASR components, as seen in existing literature [7], [8]. Our research suggests that despite the distinct outputs of these two components, they share similar technical principles and vulnerabilities that can be exploited by attackers. Thus, analyzing them separately may obscure the full understanding of the potential attack vector.

To address these classification challenges, our work proposes a novel categorization of attacks based on the VCS architecture, dividing them into attacks on the physical layer, data layer, model layer, and service layer, as outlined in Figure 3. This approach allows for a more precise identification of the vulnerabilities specific to each layer. We will also categorize defense solutions accordingly. Those designed to protect specific layers will be discussed in their respective sections, while generalized defense strategies applicable across all VCS layers will be comprehensively covered in Section VII. The following sections will provide a detailed analysis of the attack threats and corresponding countermeasures for each layer within the VCS.

III. Physical Layer

The physical layer of VCS plays a pivotal role in converting acoustic signals into digital formats. This conversion process involves the transmission of acoustic signals through channels to microphone devices, which are then digitized. However, this layer is vulnerable to a range of attacks due to the lack of signal verification in the transmission channel and the susceptibility of microphone devices to manipulation. Attackers can exploit these vulnerabilities by transmitting malicious audios or using specific signals to make microphones generate attacker-desired digital signals. This section explores various attack types targeting the physical layer, including transduction attacks that manipulate physical components to create false inputs and voice-synthesis attacks that craft misleading audio inputs, A comprehensive summary and comparison of these attacks are detailed in Table 2, presenting their methods, targets, and potential impacts on VCS.

1. Transduction attacks in physical layer

Transduction attacks exploit microphone vulnerabilities in VCS by using non-standard signals that microphones should typically not recognize. These attacks manipulate the physical properties of microphone equipment to induce unintended digital signal genera-

tion, leading to VCS compromise.

Light signal Microphones, designed to be sensitive only to sound signals, can unexpectedly respond to modulated light signals. Sugawara *et al.* [1] demonstrated that by modulating laser amplitude, attackers can transmit malicious commands to VCS from distances exceeding 100 m, exploiting this unintended sensitivity.

Electromagnetic wave (EW) Microphone circuits can inadvertently act as antennas, receiving EWs which are then demodulated into malicious commands. This vulnerability allows attackers to use electromagnetic coupling, as shown by Kasmi and Esteves [40], to control voice assistants through headphone cables. Further research indicates that specific EWs generated by wired [41] or wireless chargers [42] can also inject commands into VCS.

Defense schemes against transduction attacks For light-based attacks, sensor fusion technology [43] offers a software-level defense by exploiting the difference between the omnidirectional nature of sound and the directional nature of light, which typically affects only one microphone. This approach detects discrepancies between multiple microphone inputs. Hardware solutions include shielding microphones with opaque covers to block light, but this may attenuate sound signals [44]. Against EW attacks, sensors detecting electromagnetic changes can alert to potential intrusions. A comprehensive defense strategy involves adding authentication mechanisms to VCS, effectively mitigating various transduction attacks.

2. Voice-synthesis attacks in physical layer

Voice-synthesis attacks in the physical layer of VCS differ from transduction attacks as they primarily utilize ultrasonic signals, which are inaudible to humans but can be received by most microphones. These attacks exploit the fact that ultrasound can be demodulated in the system through nonlinear amplifiers after being received by the microphone. Attackers modulate malicious commands into these ultrasonic signals, leading to interference with normal functions of VCS. Researchers have demonstrated such attacks using solid surface transmission [45] and air transmission methods [38], [46]–[53]. Additionally, an innovative method has been proposed that leverages specific current fluctuations to remotely attack VCSs using acoustic waves generated by switching mode power supplies (SMPS) within the same power grid [54].

Defense schemes against voice-synthesis attacks To counteract these attacks, hardware-based defenses include using microphones that are incapable of receiving ultrasonic signals, similar to the iPhone 6 Plus microphone [46], or implementing a "guarding" mechanism or "voice cloaks" with an external signal generator to neutralize malicious audio [55], [56]. However, replacing microphones or adding signal generators in existing VCS products is impractical, making software-level defenses more viable. For air-transmitted voice-synthesis attacks, the demodulated attack signal in the 500–1000 Hz range differs significantly from the original signal, detectable via a variational auto-encoder [57]. Additionally, a microphone array can calculate the attenuation rate of sound waves at different microphones, identifying ultrasonic-origin voice commands [58]. Solid surface attacks lack this attenuation distinction, but their recovered attack signal introduces new frequency components from 10 kHz to 20 kHz, providing another basis for detection and differentiation from baseband signals.

IV. Data Layer

In VCS, the data layer is essential for refining the digital signals obtained from the physical layer. Its primary function is to filter and enhance audio signals, which often contain a mix of human voices and background

Table 2 Comparison of transduction attack and voice-synthesis attack in physical layer

Attack type	Article	Signal	Attack target	Attacker vector	Performance	
					Success rate (%)	Distance
Transduction attacks	Sugawara *et al.* [1]	Light	Microphone	Over-the-air	90	25 m
	Kasmi *et al.* [40]	EW	Headphone cable	Over-the-air	Not avaliable	Not avaliable
	GhostTalk [41]	EW	Charging Port	Power line	100	Not avaliable
	Dai *et al.* [42]	EW	Microphone	Over-the-air	91	5 cm
Voice-synthesis attacks	Surfingattack [45]	Ultrasonic	Microphone	Solid Surface	100	2.5 m+
	Dolphinattack [38]	Ultrasonic	Microphone	Over-the-air	100	165 cm
	Iijima *et al.* [47]	Ultrasonic	Microphone	Over-the-air	100	10 m
	Capspeaker [48]	Ultrasonic	Capacitor	Over-the-air	80	10.5 cm
	Roy *et al.* [49]	Ultrasonic	Microphone	Over-the-air	50	760 cm
	Song *et al.* [50]	Ultrasonic	Microphone	Over-the-air	80	3 m
	Yan *et al.*[51]	Ultrasonic	Microphone	Over-the-air	100	165 cm
	Nuit [46]	Ultrasonic	Microphone	Over-the-air	100	360 cm
	Yang *et al.* [54]	Audible sound	SMPS	Over-the-air	90	23 m

noise. Voice activity detection algorithms, like G.729 [59], are used to isolate segments containing human speech, followed by the application of low-pass filters to reduce noise and improve VCS's recognition capabilities. Advances in Deep Neural Networks (DNN) have further enhanced these preprocessing tasks [26], [60]. Besides noise reduction, this layer is responsible for extracting relevant features from audio signals using techniques such as delta frequency cepstral (DFC), mel-frequency cepstral coefficients (MFCC), linear predictive coding (LPC), mel-frequency cepstral smoothing (MFCS), and perceptual linear prediction (PLP), preparing them for subsequent phoneme, character, or word sequence recognition. However, vulnerabilities within these feature extraction processes have been identified, allowing attackers to execute voice-synthesis attacks and adversarial attacks. This section discusses these attacks, exploring how they exploit the data layer's weaknesses. Table 3 provides a comparative summary of these attacks, outlining their strategies and impact on VCS.

1. Voice-synthesis attacks in data layer

Voice-synthesis attacks in the data layer of VCS utilize technology to create specific speech patterns that can be misinterpreted as legitimate instructions. Due to the lossy nature of signal processing and feature extraction in this layer, attackers can craft voice segments that mimic target voice features. These segments are then mistakenly recognized as intended voice signals by the VCS after undergoing preprocessing. A key characteristic of these attacks is the significant difference between the synthesized and target audio signals, making detection challenging for users.

For instance, Bispham *et al.* [61] produced nonsensical voice commands by altering consonant phonemes in the target voice. Despite the apparent errors, the VCS's voice model could correct these anomalies, leading to system recognition of these commands. Abdullah *et al.* [62] employed various signal processing techniques like time domain inversion and high frequency addition to morph the target voice into an unintelligible audio signal. They leveraged the VCS's sensitivity to specific keywords to construct more effective malicious samples. In another approach, Carlini *et al.* [39] and Vaidya *et al.* [63] targeted the MFCC feature extraction, common in VCS. By calculating MFCC features of the target voice and then reversing this process, they generated synthetic audio that successfully deceived the VCS. While these attacks effectively disguise their intent, the unusual noises they produce may still raise user suspicion. Therefore, Ji *et al.* [64] proposed a new attack that purely speeds up or slows down original audio instead of adding perturbations to inject malicious voice commands.

Defense schemes against voice-synthesis attacks Defending against voice-synthesis attacks in the data layer involves two strategies: detection and prevention. Detection refers to the system's ability to recognize an attack and alert the user. One common approach is the use of verification mechanisms such as CAPTCHAs [65], where the system requests a verification response from the user before executing a voice command. This allows users to confirm whether the command aligns with their intentions. Additionally, prompt warnings can notify users when the VCS receives voice commands, providing an opportunity to recognize and counteract potential attacks, even if the user may overlook the unusual noise generated by the attack [39].

Prevention strategies focus on averting the damage from an attack. Voice activity detection (VAD) is proposed as a preventive measure [62]. As a speech processing algorithm, VAD can distinguish between noise and actual speech [66], [67], effectively identifying and disregarding synthesized audio attacks. Moreover, adjusting VCS filters to slightly degrade audio quality can disrupt synthetic audio, which typically lacks robustness, while still preserving the recognition of genuine human speech [39]. These preventive measures operate by exploiting the inherent weaknesses in synthesized audio, thereby reducing the probability of successful attacks.

2. Adversarial attacks in data layer

Originally emerging in the field of image recognition [68], the concept of adversarial attacks has gained significant attention in speech recognition. Contrary to voice-synthesis attacks, adversarial attacks craft voice commands that sound normal to human users but lead to incorrect predictions by the machine learning models in VCS. These attacks typically involve introducing subtle perturbations into benign audio samples, creating what are known as adversarial samples. These samples exploit the sensitivity of deep learning models to small input changes, posing serious security and privacy risks to audio-based systems [69], [70].

In audio applications, these perturbations can be added directly to the audio waveform or to its features. When perturbations are applied to audio features, attackers must reverse-engineer the audio waveform from these features to ensure the altered audio is still recognizable by the VCS. This subsection focuses on adversarial attacks that perturb audio features, as this method intricately involves the operational principles of the data layer in VCS. Such attacks highlight the inherent vulnerabilities in the feature extraction and processing mechanisms, underscoring the need for robust defense strategies in this layer of VCS.

1) Taxonomy of adversarial attacks in VCS

Adversarial attacks in VCS can be classified based on different criteria, including attack scenario, attack target, and target vector.

Attack scenario Adversarial attacks are divided into white-box, black-box, and gray-box attacks based on the attacker's knowledge of the target VCS model. White-box attacks assume complete access to the VCS model, including its internal parameters. In contrast, black-box attacks only allow attackers to access the in-

Table 3 Comparison of voice-synthesis attacks and adversarial attacks in data layer

Attack type	Article	Attack technology	Goal	Attack target (Category)	Model knowledge	Attack vector	Cost (Time)	Performance	
								Success rate (%)	Distance
Voice-synthesis attacks	Bispham *et al.* [61]	RCP	Targeted	Google Assist (ASR)	Black	WAA	N.A.	N.A.	N.A.
	Abdullah *et al.* [62]	SP	Targeted	10 models (ASR)	Black	WTA	N.A.	100	N.A.
						WAA	N.A.	80	1 foot
				2 models (SV)		WTA	N.A.	100	N.A.
	Carlini *et al.* [39]	GD	Targeted	CMU Sphinx (ASR)	White	WAA	32 h	82	0.5 m
		IMFCC		Google Now (ASR)	Black		N.A.	80	$\leq$ 3.5 m
	Vaidya *et al.* [63]	IMFCC	Targeted	Google Now (ASR)	Black	WAA	N.A.	N.A.	N.A.
Adversarial Attacks	Houdini [71]	GD	Untargeted	DeepSpeech-2 (ASR)	White	WTA	N.A.	N.A.	N.A.
				Google Voice (ASR)	Black				
	Iter *et al.* [14]	GD	Targeted	WaveNet (ASR)	White	WTA	N.A.	N.A.	N.A.
	Yakura *et al.* [15]	GD	Targeted	DeepSpeech (ASR)	White	WWA	N.A.	50–100	$\leq$ 0.5 m
						WAA		60–90	
	Chang *et al.* [72]	RNN	Targeted	KWS (ASR)	White	WAA	$\approx$ 0.096 s	84.30	$\leq$ 4 m
	Kreuk *et al.* [73]	FGSM	Untargeted	DNN End-to-end (SV)	White	WTA	N.A.	64–94 (FAR)	N.A.
					Black			46 (FAR)	
	Li *et al.* [74]	FGSM	Untargeted	GMM i-vector (SV)	White	WTA	N.A.	99.99 (FAR)	N.A.
					Black			< 70 (FAR)	
		Transfer		DNN x-vector (SV)	Black			< 60 (FAR)	
	Marras *et al.* [75]	GD	Targeted	VGGVox (SV)	White	WTA	N.A.	< 80	N.A.
	Wang *et al.* [76]	GD	Targeted	DNN x-vector (SV)	White	WTA	N.A.	< 98.5	N.A.
	Specpatch [77]	RCP	Targeted	DeepSpeech2 (ASR)	Black	WTA	N.A.	100	N.A.
						WAA		80	1 m
	Wang *et al.* [69]	GD	Targeted	6 models (ASR)	Black	WAA	N.A.	< 91.7	10 cm

Note: RCP: replacing the consonant phonemes. SP: signal processing. GD: gradient descent. IMFCC: inverse MFCC. FGSM: fast gradient sign method. FAR: false acceptance rate. N.A.: not avaliable.

puts and outputs of the VCS, without gaining access to internal model details. Gray-box attacks represent an intermediate scenario, where the attacker has partial knowledge of the model's parameters.

Attack target In terms of objectives, adversarial attacks can be categorized into targeted attacks and untargeted attacks. Targeted attacks manipulate the VCS to produce a specific, incorrect output defined by the attacker. In contrast, untargeted attacks aim to induce any error in the system's output without a predetermined result. For example, for SV, untargeted attacks might result in the identification of any incorrect speaker, while targeted attacks would misidentify a speaker as a specific individual chosen by the attacker. Similarly, in ASR, untargeted attacks cause any incorrect transcription, whereas targeted attacks aim for a specific false transcription.

Attack vector Based on the transmission medium, adversarial attacks in VCS can be categorized into wav-to-API (WTA) attacks and wav-air-API (WAA) attacks [78]. WTA attacks involve directly feeding an adversarial audio file into the VCS API, while WAA attacks transmit the adversarial sample through the air, capturing it with the system's microphone, and then process it. Additionally, there is a wav-wave-API (WWA) attack, where adversarial audio deceives VCS after transmission through the transmitter and radio play [15]. This classification aids in understanding how adversarial audio affects VCS, indicating the need for diversified defense strategies.

2) Basic idea of designing adversarial samples

Adversarial audio samples are essentially a fusion of benign audio with carefully crafted adversarial perturbations. The primary challenge in the industry is to ensure that these perturbations, when added to benign audio, remain imperceptible to human users while effectively leading the VCS to produce erroneous outputs [79]. This task can be conceptualized as an optimization problem where the attacker's goal is to minimally alter the audio to cause misclassification by the VCS.

The process of designing such attacks in the audio domain, similar to other domains, often involves training neural networks [11]. However, the methods used in the image recognition domain, the most prevalent area of adversarial attacks application, are not directly transferable to audio due to fundamental differences. In audio, perturbations are added in the temporal domain requiring higher precision compared to the spatial do-

main in images [80]–[84].

The optimization problem in this context is expressed as follows:

$$F(x,\delta,y)=\min_{\|\delta\|} l_m(f(x+\delta),y)+c\cdot\|\delta\| \quad (1)$$

where x represents the benign audio sample, δ is the added perturbation, and y is the label output by the model $f(\cdot)$. The loss function $l_m(\cdot)$ measures the discrepancy between the model's actual output $f(x+\delta)$ and the label y. The term $c\cdot\|\delta\|$ quantifies the perturbation's impact on the original audio, where c is a balancing coefficient between attack effectiveness and audio quality. Higher values of c indicate substantial degradation in audio quality, potentially compromising the integrity of the original content.

For untargeted attacks, the attacker seeks the smallest δ that drastically alters the output $f(x+\delta)$ from y (given $f(x)=y$). Conversely, for targeted attacks, the goal is to minimize δ such that $f(x+\delta)$ closely matches a specified target output y' (where $f(x)\neq y$).

To address the inherent optimization problem in designing adversarial attacks in the data layer, several methods, primarily centered around gradient descent and deep learning techniques, have been proposed in the industry.

Gradient descent Gradient descent (GD) is a primary method for creating adversarial audio, widely studied in current research [14], [15], [71], [69], [85]. GD optimizes adversarial samples by iteratively calculating the local minimum of a loss function using partial derivatives and the chain rule. Typically utilized in white-box attack scenarios, GD requires an understanding of the target loss function's specifics. Although increasing the number of iterations can enhance the success rate of the attack, it may also compromise the quality of adversarial audio [86].

Deep learning-based methods To overcome the time and computational resource constraints of iterative GD, deep learning models, such as RNNs [72], are employed. These pre-trained models simulate the gradient descent process, enabling real-time generation of adversarial samples, thus enhancing efficiency.

Fast gradient sign methods Fast gradient sign method (FGSM), introduced by Goodfellow *et al.* [68], offers a faster approach to generate adversarial samples. It involves adding perturbations in the gradient direction of the original audio using a sign function, requiring only a single gradient calculation and addition/subtraction operation. Proven effective in the audio domain, FGSM can efficiently produce adversarial samples [73], [74].

Transferability of adversarial samples Given the limited access to commercial VCS models, attackers often rely on gray-box or black-box approaches, relying on querying the model and interpreting outputs. Transferability of adversarial samples between models becomes crucial in such scenarios. Studies in computer vision have shown the effectiveness of transferring adversarial samples across different models [87]–[90]. In audio, the success of transfer-based attacks is linked to the similarity between the parameters and structures of different models [91]–[93]. Li *et al.* [74] demonstrated this by successfully executing a transfer-based adversarial attack between i-vector and x-vector models, exploiting their structural similarities. Yao *et al.* [93] proposed a spectral transformation attack based on a modified discrete cosine transform to improve the transferability of adversarial voices to black-box victim models.

3) Characteristics of adversarial attacks in data layer

A key characteristic of adversarial attacks in the data layer is the indirect addition of perturbations. Rather than directly altering the audio signal, attackers inject perturbations into neural network features, such as those obtained from STFT or MFCC. For STFT-based approaches, benign audio is first converted into a spectrogram, and adversarial perturbations are added at this stage, followed by inverse transformation to generate adversarial audio [71], [72]. In contrast, while perturbing MFCC features can mitigate some challenges, the lossy nature of the inverse MFCC transformation leads to a significant degradation in the quality of adversarial audio [14], [15], [94].

4) Defense schemes against adversarial attacks

Adversarial training, a method proven effective in image processing, involves integrating adversarial examples into training data to enhance model robustness [95]. However, this approach has limitations:

i) It can lead to decreased accuracy in predicting legitimate examples due to label leakage [12].

ii) The effectiveness of adversarial training depends on the availability of a diverse set of known adversarial examples, making it less effective against novel attacks [13].

iii) This method increases training iterations, thereby raising the model's training cost.

Given that these attacks often require in-depth knowledge of the VCS's preprocessing techniques, they are generally categorized as white-box attacks. A counter-strategy involves modifying the targeted data preprocessing methods. For example, if attacks primarily target MFCC processing, alternative feature extraction techniques (e.g., neural networks) may be employed [16], [17]. Du *et al.* [96] designed a unified preprocessing mechanism to disrupt the continuity and transferability of adversarial attacks and an adaptive ASR transcription method to further bolster the defense strategy. Park *et al.* [97] demonstrated that carefully selected noise can considerably influence the transcription results of adversarial audio examples while having minimal impact on the transcription of benign audio waves. Introducing new neural network modules to the data layer may inadvertently create new vulnerabilities within the system.

V. Model Layer

In VCS, the model layer plays a crucial role in decoding audio feature vectors processed in the data layer. This decoding is traditionally achieved through an acoustic model, which translates feature vectors into phonemes, and a language model, predicting word sequence probabilities to output the most probable sentence. Historically, decoding methods have included hidden Markov models, recurrent neural networks, and N-gram models. However, the rise of deep learning technologies has led to advanced models like Wav2Letter (CNNs-based), Kaldi (DNN-HMM), and CMU Sphinx (GMM-HMM) becoming mainstream due to their enhanced accuracy in speech recognition [98]. Despite these advancements, the model layer remains vulnerable to adversarial attacks that manipulate the decoding process and spoofing attacks, where attackers mimic legitimate audio inputs to deceive the system, highlighting the need for robust security measures in this critical component of VCS.

1. Spoofing attacks in model layer

Spoofing attacks in the model layer of VCS primarily target the SV component. These attacks are executed with the intention of impersonating a target speaker to gain unauthorized access or privileges within the VCS system [99], [100]. Commonly, spoofing attacks are categorized into four types: replay, impersonation, voice synthesis, and voice conversion.

1) Replay

A replay attack involves recording a victim's voice using a recording device and then replaying this captured audio to deceive the SV system. This method is straightforward yet highly effective, posing a significant threat to various SV systems due to its simplicity and reliability. The effectiveness of replay attacks has been demonstrated against many types of SV systems [101]–[104].

2) Impersonation

Impersonation attacks are executed by an attacker manually imitating the voice patterns and speech behavior of the target individual, without the aid of any computerized devices. These attacks aim to trick the SV component into falsely recognizing the attacker as the target. Research has indicated that even non-professional impersonators can be successful, particularly if they are familiar with the target's voice pattern or possess a naturally similar voice [105], [106]. Professional impersonators often try to replicate rhythmic features of the target's speech to enhance the deception [107]. However, it has been observed that significant differences between the impersonator's and the target's natural voice can still be detected by SV systems [108], [109].

3) Voice synthesis

Voice Synthesis (VS) is a technology that aims to generate speech resembling the victim's voice from input text, distinct from standard TTS applications. We can also call voice synthesis as voice cloning [110] here. The goal is to deceive the SV component by impersonating the victim. Traditional VS techniques include unit selection [111], statistical parametric modeling [112], and hybrid approaches combining both [113]. Advancements in deep learning have led to the use of neural networks in VS, such as generative adversarial networks (GAN) for enhancing speech quality [114]–[116], and specific models like WaveNet [117], [118] and Tacotron [119] for victim-specific speech generation.

4) Voice conversion

Voice conversion (VC) differs from VS as it transforms the attacker's speech to match the victim's speech patterns. Traditional VC methods use statistical models such as HMM [120], GMM [121], principal component analysis (PCA) [122], and non-negative matrix factorization (NMF) [123]. Modern approaches leverage neural networks, including artificial neural networks (ANN) [124], WaveNet, and GANs. Recent research has focused on challenges such as low-resource languages [125], [126] and cross-lingual voice conversion [127]. Innovative techniques involving specially designed tubes have been explored to bypass liveness detection systems by modifying the attacker's voice to resemble the victim's voice [128].

5) Twins

Identical twins present a unique challenge in SV due to their highly similar speech characteristics. While SV systems are generally effective in distinguishing between different individuals, they struggle to differentiate between identical twins. Studies have indicated that twins share similar speech signal patterns, pitch contours, formant contours, and spectrograms [129], [130], leading to higher false acceptance rates (FAR) in SV. Incidents have been reported where twins were able to access each other's accounts by bypassing SV checks [131].

6) Defense schemes against spoofing attacks

Defense strategies against spoofing attacks in VCS primarily focus on identifying distortions in audio signals during transcription.

For replay attacks Techniques have been developed to distinguish between original and replayed audio by analyzing far-field recordings characteristic of distant attacks [103], [132]. Another approach involves maintaining a database of previous audio recordings in VCS and calculating similarity scores for new inputs to detect replays [133].

For voice synthesis Traditional VS detection methods often rely on understanding acoustic differences based on specific VS algorithms, such as analyzing spectral parameter ranges [134] and variations in mel-cepstral coefficients [135]. Differences in pitch patterns and vocal tract models between human-produced and synthesized audio offer additional detection markers [136]–[139]. For example, Liu *et al.* [139] designed

a defense scheme to protect the speaker's voice from voice synthesis attacks by modifying the target speaker's speeches in the frequency domain before publishing them or sending them to others. In addition, Zhang *et al.* [140] proposed a robust deepfake speech detection method that employs feature decomposition to learn synthesizer-independent content features.

For voice conversion Defenses against VC attacks draw inspiration from VS defense strategies, with studies showing that support vector machine (SVM) classifiers based on super-vectors demonstrate inherent robustness against VC [141], [142]. Analyzing pairwise distances between continuous feature vectors in human versus VC-generated audio has also proven effective.

Machine learning-based approaches State-of-the-art methods involve using machine learning models to discern spectral differences between human and generated audio [143]–[148]. The ASVspoof challenges have been instrumental in driving advancements in anti-spoofing technology, with RawNet2 emerging as a successful model in this domain [149]–[153]. Additionally, research that combines articulatory phonetics to reconstruct vocal tracts from audio signals has demonstrated potential in distinguishing between human and machine sources [154], [155]. A novel approach proposed in [156] shifts the focus from preemptively rejecting VC-generated audio to reconstructing the source speaker's voiceprint for attacker identification.

2. Adversarial attacks in model layer

The model layer of VCS, much like the data layer, is vulnerable to adversarial attacks. However, the attack methodology in the model layer typically involves directly adding adversarial perturbations to the audio waveforms of legitimate audio samples. This direct manipulation of audio waveforms distinguishes these attacks from those in the data layer. Adversarial attacks in the model layer pose a significant challenge to audio classifiers, often leading to misclassifications and subsequent security breaches. A detailed summary and comparative analysis of recent advancements in adversarial attacks targeting the model layer can be found in Table 4. This table provides insights into the various techniques and strategies employed in these attacks, underlining their potential impact on VCS performance and security.

1) Adversarial examples crafting

In the model layer of VCS, the shift towards black-box

Table 4 Comparison of voice-synthesis attacks and adversarial attacks in model layer. This table provides insights into the various techniques and strategies employed in these attacks, underlining their potential impact on VCS performance and security (N.A.: not avaliable)

Attack type	Article	Attack technology	Goal	Attack target (Category)	Model knowledge	Attack vector	Cost (Time)	Performance	
								Success rate (%)	Distance
Adversarial attacks	Schönherr *et al.* [87]	GD	Targeted	Kaldi (ASR)	White	WTA	2 min	98	N.A.
	Qin *et al.* [157]	GD	Targeted	Lingvo (ASR)	White	WTA	N.A.	100	N.A.
						WAA		60	
	Taori *et al.* [158]	GD+GA	Targeted	DeepSpeech (ASR)	Black	WTA	N.A.	35	N.A.
	Neekhara *et al.* [159]	GD	Targeted	2 model (ASR)	White	WTA	N.A.	89.6	N.A.
	Kwon *et al.* [160]	GD	Targeted	DeepSpeech (ASR)	White	WTA	1 h	91.7	N.A.
	Li *et al.* [79]	GD	Targeted	Amazon Alexa (ASR)	Gray	WAA	N.A.	50	7.7 ft
	Gong *et al.* [161]	RL+RNN	Untargeted	KWS (ASR)	Gray	WTA	0.15 s	43.5	N.A.
	Liu *et al.* [162]	GD	Targeted	DeepSpeech (ASR)	White	WTA	4 min–5 min	N.A.	N.A.
	Imperio [163]	GD	Targeted	Kaldi (ASR)	White	WAA	80 min	25	3 m
	Szurley *et al.* [164]	GD	Targeted	DeepSpeech (ASR)	White	WAA	N.A.	N.A.	6 in
	Han *et al.* [165]	GA	Untargeted	Google Cloud (ASR)	Black	WTA	N.A.	86	N.A.
	Khare *et al.* [166]	GA	Untargeted	2 models (ASR)	Black	WTA	N.A.	N.A.	N.A.
			Targeted						
	Wu *et al.* [167]	GA	Targeted	Kaldi (ASR)	Gray	WTA	N.A.	90	N.A.
	AudiDoS [168]	GD	Untargeted	2 models (ASR)	White	WAA	N.A.	78	30 cm
	Chen *et al.* [91]	GD	Targeted	4 models (ASR)	Black	WAA	N.A.	98	2 m
		Transfer		Apple Siri (ASR)				N.A.	N.A.
	Metamorph [169]	GD	Targeted	DeepSpeech (ASR)	White	WAA	5 h–7 h	90	6 m
	Wang *et al.* [170]	GAN	Targeted	2 models (ASR)	White	WTA	0.009 s	92.33	N.A.
	Wang *et al.* [171]	GA	Targeted	DeepSpeech (ASR)	Gray	WTA	N.A.	98	N.A.
	Advpulse [172]	GD	Targeted	KWS (ASR)	White	WAA	N.A.	89.9	3 m
				DNN x-vector (SV)				89.3	

Table 4 (Continued)

Attack type	Article	Attack technology	Goal	Attack target (Category)	Model knowledge	Attack vector	Cost (Time)	Performance	
								Success rate (%)	Distance
Adversarial attacks	Abdullah *et al.* [84]	SP	Untargeted	7 models (ASR)	Black	WTA	N.A.	100	N.A.
				Microsoft Azure (SV)				N.A.	
	SirenAttack [94]	PSO	Untargeted	DeepSpeech (ASR)	White	WTA	N.A.	100	N.A.
			Targeted	7 models (ASR)	Black			95.25	
				7 models (SV)				99.45	
	Chen *et al.* [173]	NES+BIM	Untargeted	3 models (SV)	Black	WAA	N.A.	100	2 m
			Targeted					95	
			Targeted	Talentedsoft (SV)		WTA		100	N.A.
		Transfer	Untargeted	Microsoft Azure (SV)		WAA		57	2 m
			Targeted					34	
	Wang *et al.* [174]	FGSM	Untargeted	GE2E (SV)	White	WTA	N.A.	N.A.	N.A.
	Xie *et al.* [175]	SP	Targeted	DNN x-vector (SV)	White	WAA	0.015 s	90	5 m
	Li *et al.* [176]	FGSM	Untargeted	DNN x-vector (SV)	White	WTA	N.A.	99	N.A.
						WAA		100	1 m
			Targeted			WTA		96.01	N.A.
						WAA		50	1 m
	Li *et al.* [177]	GN	Untargeted	SineNet (SV)	Gray	WTA	N.A.	N.A.	N.A.
			Targeted						
	Zhang *et al.* [178]	GD	Targeted	VGGVox (SV)	Gray	WTA	N.A.	100	N.A.
				Microsoft Azure (SV)	Black			75	
		Transfer		Apple Homekit (SV)		WAA		67.5	
	Li *et al.* [179]	ATN	Targeted	SineNet (SV)	White	WTA	0.042 RTF	N.A.	N.A.
	FoolHD [180]	GCA	Untargeted	DNN x-vector (SV)	White	WTA	N.A.	99.6	N.A.
			Targeted					99.2	
	SMACK [181]	GA + GE	Targeted	5 models (ASR)	Black	WTA	474 s	87.7	N.A.
						WAA	N.A.	43.3	200 cm
				2 models (SV)		WTA	525 s	99.2	N.A.
						WAA	N.A.	35.8	200 cm
	Zheng *et al.* [182]	CC-CMA-ES	Targeted	5 models (ASR)	Black	WTA	N.A.	100	N.A.
				2 models (SV)					
		DNN		5 models (ASR)		WAA		60	15 cm
	Liu *et al.* [183]	GE	Targeted	4 models (ASR)	Black	WNA	362.18 s	87.7	N.A.

Note: GD: gradient descent. GA: genetic algorithm. SP: signal processing. PSO: particle swarm optimization. NES: natural evolution strategy. BIM: basic iterative method. FGSM: fast gradient sign method. GN: generative network. ATN: adversarial transformation network. GCA: convolutional auto-encoder. CC-CMA-ES: cooperative-coevolution covariance-matrix-adaptation evolution-strategy. GE: gradient estimation. RTF: real-time factor, the ratio of the processing time to the input duration. N.A.: not avaliable.

models has made traditional gradient-based adversarial sample generation methods like GD and FGSM less effective. To address this, researchers have developed gradient-agnostic algorithms for crafting adversarial examples.

Genetic algorithm (GA) GA employs a search-based approach, iterating through potential samples to deceive machine learning models. By using techniques like crossover and mutation, GA refines search results, prioritizing samples with higher fitness scores for subsequent iterations. This method is suitable for gray-box or black-box attacks due to its reliance solely on model output rather than gradient information [158], [165]–[167], [171]. However, GA's iterative nature leads to high computational resource demands.

Particle swarm optimization (PSO) Originating from swarm intelligence, PSO mimics collective animal behaviors to search for optimal solutions [184]. In adversarial example generation, samples are treated as swarm particles, moving towards the most effective position in the search space iteratively [94]. PSO benefits from fast convergence and does not require gradient information, making it efficient for gray-box and black-box attacks.

Ensemble algorithm Chen *et al.* [173] introduced a novel black-box approach combining the natural evolution strategy (NES) [185] and the basic iterative method (BIM) [186]. NES estimates the gradient of the black-box model, and this estimated gradient is then used in BIM to generate adversarial examples iteratively. This method efficiently crafts adversarial examples suitable for black-box settings. Fang *et al.* [187] proposed a sequential ensemble optimization algorithm, which iteratively optimizes the adversarial perturbation on each surrogate model, leveraging collaborative information from other models. This is a transfer-based adversarial attack on ASR systems in the zero-query black-box setting.

Deep learning-based methods Approaches like the gated convolutional auto-encoder (GCA) [180], adversarial transformation network (ATN) [179], and generative network (GN) [177], [188] employ deep learning for adversarial example generation. GN is effective in gray-box model attacks, while ATN significantly reduces the time required to generate adversarial examples. Zuo *et al.* [189] designed an adversary sample attack on the speaker identification system using multiple utterances.

Remark 1 Communication and video conferencing through IP have become the primary means of community communication nowadays. In the work in [183], researchers discovered that due to the special characteristics of IP channels, audio signal transmission can cause signal attenuation, random channel noise, and other interferences, which can affect the effectiveness of audio adversarial samples. Therefore, in future research, it is necessary to focus on investigating the potential impact of malicious audio in the transmission process over IP channels. In this paper, we refer to attacks that are transmitted through IP channels as wav-network-API (WNA).

2) Defense schemes against adversarial attacks

The nature of attacks targeting the model layer demands additional strategies. Since these attacks are typically directed at the model itself, the transferability of adversarial examples between different models tends to be limited. Zeng *et al.* [18] observed that adversarial examples crafted for one specific model often yield different prediction results when applied to another model, a discrepancy not seen with normal audio signals. This unique behavior of adversarial examples provides a basis for detecting and countering attacks in the model layer. By exploiting the differences in model responses to adversarial versus normal audio, defense mechanisms can be designed to effectively identify and mitigate adversarial attacks targeting this crucial layer of VCS.

VI. Service Layer

The evolution of VCS has led to the integration of third-party services, enhancing functionality beyond basic speech content recognition or identity verification. Examples include Amazon Echo and Google Assistant. Although this expansion addresses user demands, it also introduces more security risks. This section explores the potential vulnerabilities and threats posed by these third-party integrations in VCS.

1. Squatting attacks in service layer

Despite mandatory reviews for third-party services in VCS to ensure compliance with security and privacy policies, many services still breach these regulations [190], [191], and current review processes struggle to identify such violations [192]. This oversight allows attackers to introduce malicious services, posing significant privacy risks. Squatting attacks occur when attackers create services with names resembling legitimate ones, deceiving users into accessing these malicious options instead. There are two primary methods of squatting attacks:

i) Similar sounding service names: Attackers may design service names phonetically similar to legitimate ones, leading to accidental activation of the malicious service. For instance, a service named "Capital Won" could be mistaken for "Capital One", especially in noisy settings or based on user dialect or gender [3], [4].

ii) Exploiting the longest matching rule: VCS typically matches service names using the longest matching rule. Attackers leverage this and user habits to construct squatting attacks. Since many users add polite terms like "please" to service commands, a malicious service named "Capital One Please" could be preferentially activated over the intended "Capital One" service, as observed in user habit surveys [4].

These squatting tactics demonstrate the vulnerabilities introduced by third-party service integration in VCS, highlighting the need for more robust security measures.

Misunderstanding attacks A misunderstanding attack is a specific form of squatting attack where the goal is not to activate a malicious service, but to induce errors within a legitimate service. These attacks exploit the limitations of VCS in accurately interpreting words outside their programmed understanding [193]. For example, Siri might misinterpret "bank" in the context of "river bank". Bispham *et al.* [61] demonstrated that by altering a single word in a command, VCS can be misled. In a banking service, changing "money" to "dough" in the query "how much money do I have?" could result in unintended information disclosure due to "dough" being slang for money. The NLU's Intent Classifier, which uses fuzzy matching to accommodate user speech variations, is often the exploitable component in such scenarios [194].

Defense schemes against squatting attacks Squatting attacks often involve similar-sounding service names or variants to trick VCS. Zhang *et al.* [4] developed a phoneme-based service name scanner to identify suspicious third-party services. Additionally, it is suggested that service platform providers analyze new services for potential naming conflicts or utilize interactive tools for policy violation detection [3], [195].

2. Faking termination in service layer

Users' misunderstandings about service termination protocols in VCS like Alexa and Google Assistant can be exploited. Users often assume that services end automatically after silence or a farewell response. However, malicious services can simulate termination sounds while remaining active, posing significant security risks if users then disclose private information or issue commands. Such deceptive practices highlight the need for greater awareness and more explicit termination protocols in VCS [4].

Defense schemes against faking termination To mitigate the risks associated with faking termination in VCS, various studies recommend enhancing service publishing authentication mechanisms [190], [192]. Service platform providers should conduct thorough word-based or phoneme-based reviews of new services to avoid confusion with existing ones. Additionally, methods such as voice interaction analysis and backend code review are effective in identifying privacy breaches or discrepancies between a service's functionality and its description. Recent research suggests that context-sensitive detectors could effectively identify instances of faking termination [4]. Notably, a proposed hardening framework for VCS in [196] focuses on ensuring that data collected by microphones is used only for local processing unless explicitly permitted by the user, thereby safeguarding against privacy data leakage caused by faking termination.

VII. General Attack Mitigation Strategy

In earlier sections, we discuss defense strategies that primarily focus on countering specific types of attacks in VCS. This section shifts the focus to state-of-the-art general attack mitigation strategies that are capable of defending against more attacks, encompassing different types and layers. These comprehensive strategies are essential for providing a more holistic defense mechanism for VCS. We have systematized existing general attack mitigation strategies and evaluated their efficacy against various attack types and characteristics. The comparative analysis of these strategies, including their strengths and limitations in resisting different forms of attacks, is presented in Table 5. This systematic overview aims to guide researchers and practitioners in selecting and implementing effective, multi-faceted defense strategies for VCS.

Table 5 Capability of defending against different attacks in different layers

Defense schemes		Attacks								Papers
		Physical layer		Data layer		Model layer		Service layer		
		TA	VsA	VsA	AA	SpA	AA	SqA	FT	
Liveness detection	Speaker characteristics	⊗	⊕	⊕	⊕	⊕	⊕	⊗	⊗	[197]–[202]
	Human voice characteristics	⊕	⊕	⊕	⊕	⊕	⊕	⊗	⊗	[200], [203]–[216]
	Active interaction	⊕	⊕	⊕	⊕	⊕	⊕	⊙	⊙	[1], [39], [217], [218]
Audio conversion	Encoding	⊗	⊙	⊕	⊕	⊗	⊕	⊗	⊗	[219]–[222]
	Filtering	⊗	⊙	⊕	⊕	⊗	⊕	⊗	⊗	[91], [94], [223]–[225]
	Downsampling	⊗	⊙	⊕	⊕	⊗	⊕	⊗	⊗	[39], [78], [91], [94], [223], [224]

Note: TA: transduction attack. VsA: voice-synthesis attack. AA: adversarial attack. SpA: spoofing attack. SqA: squatting attack. FT: faking termination. ⊕: Defensible. ⊙: Probably Defensible. ⊗: Indefensible.

1. Liveness detection

Liveness detection has emerged as a prevalent defense strategy in VCS. It is primarily designed to ascertain whether voice commands originate from actual humans [226]–[229]. The fundamental premise behind this approach is the recognition that most malicious commands are machine-generated. These commands are typically played through speakers or directly input into the VCS API via audio files, such as WAV files. Unlike these artificially produced commands, genuine human users do not generate voice commands in this manner. Therefore, by identifying the characteristics of human speech, liveness detection aims to filter out these non-human, machine-generated inputs, thereby enhancing the security of VCS.

Passive detection In the context of liveness detection for VCS, passive detection plays a crucial role in distinguishing between human-spoken voice commands and those generated by speakers. This is achieved through the analysis of sound characteristics using two main techniques:

i) Detecting speaker characteristics: Voice commands emitted from speakers often carry unique signal distortions, which are a result of circuit noise inherent to the speaker's hardware. These distortions differ significantly from the patterns found in human speech and can be identified using classifiers trained specifically for this purpose [197]–[201]. Moreover, the electromagnetic fields generated by speakers during sound emission, owing to the electronic components, can be detected using a magnetometer in smart devices, further aiding in the determination of the voice command's origin [202].

ii) Detecting human voice characteristics: Human speech is produced through a complex physiological process involving the coordinated action of the mouth, vocal tract, vocal cord, and lungs. The airflow from the

lungs, passing through the glottis, causes vocal cord vibrations, which are then amplified by resonances in the mouth and vocal tract to form the final sound signal. Identifying features inherent to this process, such as breathing airflow patterns [200], [203]–[206], mouth movements [207]–[209], [216], as well as bone vibrations [210]–[215], [230], provides a basis for determining whether a voice command is human-generated. These features can be monitored using microphones, cameras, or other specialized sensors. In practical applications, integrating additional devices or sensors might be necessary to enhance the accuracy and reliability of such verifications.

These passive detection methods are instrumental in bolstering the security of VCS by ensuring that voice commands are genuinely human and not artificially generated or replayed through electronic devices.

Active interaction The active interaction defense scheme in VCS involves engaging users in a manner similar to a CAPTCHA to ascertain the authenticity of voice commands. A prevalent form of this scheme is the Challenge-Response mechanism. Upon receiving a voice command, VCS issues a challenge to the user, requiring an appropriate response within a predetermined time frame. Failure to respond correctly within this window leads to the assumption that the command is machine-generated, and thus, the command execution is denied [1], [39], [217]. Although effective in thwarting voice attacks to an extent, this method introduces additional steps for the user, potentially compromising the usability of the VCS.

Remark 2 Recent research [128] has demonstrated that malicious attacks can manipulate a speaker's voice commands into harmful instructions using a specially designed tube. As these commands are essentially uttered by a real person, they can effectively circumvent traditional liveness detection methods. Future research in VCS security must account for the implications of such attacks.

2. Audio conversion

The conversion of audio in the data layer of VCS, before it is passed to subsequent layers for further processing, serves as a defensive measure against voice-synthesis and adversarial attacks [83], [231]. This effectiveness stems from the conversion process's ability to disrupt the specific patterns and structures that these attacks aim to exploit or deceive. As a result, the converted audio loses the characteristics intended by the attack, rendering it ineffective. In contrast, benign audio typically exhibits greater resilience to these conversions and is only minimally affected, preserving its integrity while mitigating potential threats.

Audio encoding Encoding incoming audio has been shown to effectively diminish the success rate of malicious audio attacks. Utilizing codecs like advanced audio coding (AAC) [221], MP3 [219]–[222], Speex [221], Opus [221], adaptive multi-rate (AMR) [220], and integrated multiple codecs [218], [220] can provide a substantial level of defense against malicious audio.

Audio filtering Voice-synthesis and adversarial attacks rely heavily on precise algorithmic perturbations. Filtering these malicious audio inputs, using methods such as median filters [91], [94], [223], quantization [223], and other noise reduction algorithms [224], [225], effectively destroy these perturbations, thereby safeguarding the VCS from such attacks.

Audio downsampling Experiments have demonstrated that downsampling audio to a lower rate and then upsampling it back to a rate suitable for VCS input can effectively mitigate attack impacts. Although benign audio remains relatively unaffected, the malicious audio loses its carefully added perturbations, thus failing to achieve the intended effect on the target VCS [39], [78], [91], [94], [223], [224].

Remark 3 Audio conversion as a defense strategy exploits the resilience of benign audio to counteract the fragility of malicious audio. This process disrupts the attacker's carefully engineered perturbations. However, in a white-box scenario, attackers aware of the VCS's audio conversion methods can adjust their strategies accordingly, potentially neutralizing the defense's effectiveness.

Remark 4 As delineated in Table 5, liveness detection effectively counters a wide array of attacks, particularly those outside the service layer. Although active interaction also offers some resistance against service layer attacks, its effectiveness comes at the cost of user experience. Given this trade-off, a preferable approach would be to combine passive detection with an enhanced service release and authentication mechanism. This combination would enable a more holistic defense against the diverse types of attacks encountered in VCS, thereby optimizing both security and user experience.

VIII. Challenges and Future Directions

1. Challenges

Hardware enhancement The effectiveness of physical layer attacks in VCS often hinges on exploiting hardware vulnerabilities, particularly in microphones. However, these vulnerabilities are not uniformly present across all microphone types. A notable example is the iPhone 6 Plus, which has been shown to effectively resist voice-synthesis attacks due to its unique microphone design, as highlighted in [55]. This variability in hardware susceptibility presents significant challenges for executing consistent attacks at the physical layer.

Noise disturbance Noise disturbance is a critical factor for both attackers and defenders in real-world VCS. For attackers, ambient noise can diminish the effectiveness and reach of malicious audio. Conversely, for defenders, noise can interfere with the accuracy of defense mechanisms, such as liveness detection systems, as demonstrated in [232]. Thus, both parties must account for the impact of noise in their strategies, which

add another layer of complexity to the security landscape of VCS.

Data security VCS has permission to override other apps to perform specific functions. For example, the voice assistant will call the map application when it receives a command to navigate. As a result, VCS has more powerful access to data. It is possible for an attacker to utilize the voice assistant to access the user's sensitive data.

Model knowledge As VCS technology has evolved, commercial models have become increasingly prevalent. These models are often proprietary and not open-sourced, a strategy employed by companies to protect their intellectual property and prevent replication by competitors. This secrecy forces attackers to operate in a black-box environment, substantially lowering the success rate of adversarial attacks. Additionally, the challenge of creating universal adversarial perturbations that can produce similar attack outcomes across different models remains a significant hurdle in the realm of adversarial attacks.

2. Future directions

The challenges identified in VCS security research open avenues for future work. To enhance the robustness of both attacks and defenses in practical scenarios, we propose following directions:

Focusing on black-box attack scenarios With the rise of closed-source models in VCS, attackers in real-world scenarios should concentrate on executing successful black-box attacks. This could involve crafting adversarial perturbations specifically for black-box models or designing transferable adversarial perturbations that can be applied from a known white-box model to an unknown black-box model [233].

Targeting combined ASR and SV functions Modern VCS, such as Apple's Siri, often integrates both ASR and SV functionalities. Attackers, therefore, need to develop malicious audio capable of simultaneously compromising both ASR and SV systems. This may require the help of more targeted deep learning techniques and more detailed spectrum modification techniques.

Optimizing defense schemes With the advancement of artificial intelligence technology, techniques such as voice synthesis technology have become very inexpensive and easy to use. For example, voice cloning can be done directly online using a piece of audio. To defend against voice cloning attacks, we can take different measures at different layers to achieve cross-enhanced defense. In the physical layer, we can design and utilize unique physical structures such as microphone array fingerprints [232]. In the data layer, we have to protect our voice data from leakage or take appropriate measures before release, such as spectrum modification [139]. In the model layer, designing and optimizing models centered on adversarial learning is a viable defense strategy. In the service layer, we believe that we need to prevent the random dissemination of data across different applications. To this end, we can design unique data dissemination protocols or data calling interfaces to prevent the leakage of speech-sensitive information (e.g., tones).

Deepening multimodal defense schemes Developing authentication mechanisms for legitimate users and legitimate commands based on multimodality. Improve voice control system defense by combining human biometrics and instantaneous verification of trusted devices instead of relying only on a single voice command.

Establishing unified standards for evaluation The development of a unified standard for assessing attacks and defense mechanisms in VCS is crucial. This standard would provide reliable and consistent evaluation metrics, akin to the common vulnerability scoring system (CVSS), aiding VCS designers in accurately assessing the security landscape.

These proposed directions aim to address the evolving landscape of VCS security, encouraging a balanced approach to unveiling sophisticated attacks and designing robust defenses.

IX. Conclusion

This paper offers a thorough and methodical examination of the security landscape in VCS. We introduce a hierarchical model structure, dividing VCS into four layers: physical layer, data layer, model layer, and service layer. Within this framework, we develop a threat model and meticulously analyze the security threats unique to each layer, including transduction, voice-synthesis, adversarial, spoofing, squatting attacks, and false termination. In particular, we perform a multi-layer cross-tabulation analysis of voice synthesis attacks, which reveals the methods and mitigation measures of voice synthesis attacks. We not only identify and describe the characteristics of these threats but also assess existing defense mechanisms and propose effective defense strategy combinations to improve VCS security. Finally, we offer strategic recommendations for future research, emphasizing the need for continuous innovation to address the rapidly evolving security challenges in VCS.

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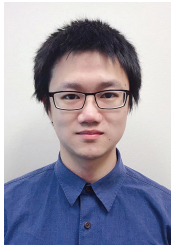

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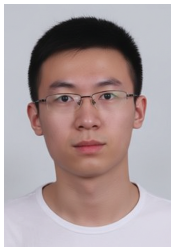

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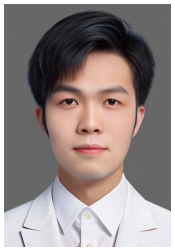

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