

Attack and Defence Modelling for Attacks via the Speech Interface

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Abstract: This paper presents a high-level model of attacks via a speech interface, and of defences against such attacks. Specifically, the paper provides a summary of different types of attacks, and of the defences available to counter them, within the framework of the OODA loop model. The model facilitates an inclusive conceptualisation of attacks via the speech interface, and serves as a basis for critical analysis of the currently available defence measures.

1 INTRODUCTION

With the growing popularity of speech-based human-computer interaction via voice-controlled digital assistants such as Google Home and Amazon Alexa, there is a need to consider the security of the speech interface, and the new challenges this mode of human-computer interaction may present for cyber security research. The speech interface is inherently difficult to secure, on account of the difficulty of controlling access to a system by sound. Whereas physical access to a system may be controlled by measures such as physical locks, and internet access can be controlled by measures such as encryption, access to a system by sound is more difficult to control. Furthermore, the speech recognition and natural language understanding technologies incorporated in voice-controlled digital assistants are designed to respond flexibly to speech input so as to ensure that interaction with users is as natural as possible. This design principle is at odds with the general cyber security principle of distrusting user input.¹

There has been a significant amount of prior work demonstrating various types of attacks which may be executed via a speech interface to gain control of a victim's system. However, there have been few attempts to conceptualise the security of the speech interface in a comprehensive framework. The contribution of this paper is to provide such a framework

using the Observe-Orient-Decide-Act (OODA) loop model. The remainder of this paper is organised as follows. Section II provides background on voice-controlled systems, on types of attacks via the speech interface and different attack scenarios, as well as on attack modelling techniques in cyber security. Section III maps the various types of attacks via the speech interface described in Section II to the OODA loop model, and reviews the defence measures currently available to counter such attacks, using the model as a framework. Section IV concludes the paper and makes some suggestions for future work.

2 BACKGROUND

Overview of Voice-Controlled Systems Following capture of the speech signal by a microphone, the architecture of a voice-controlled system typically consists of a speech recognition stage for translation of acoustic features to a sequence of words, a natural language understanding component for extraction of user intent from the word sequence, a dialogue management component which determines the action to be taken by the assistant based on the user intent and contextual information, a response generation component which constructs a verbal or non-verbal response (the non-verbal response being for example a cyber-physical action such as turning on a light), and, in the case of a verbal response, a speech synthesis component which generates an audio version of the response. This architecture is detailed for example by Lison and Meena (Lison and Meena, 2014). In the current generation of voice-

¹See for example in ENISA Info notes published 1st June 2016, "The Dangers of Trusting User Input", <https://www.enisa.europa.eu/publications/info-notes/the-dangers-of-trusting-user-input> [accessed 29th August 2018]

controlled systems, speech recognition and natural language understanding are typically performed using some form of machine learning, whereas the dialogue management component maps input from the natural language understanding component to output to be generated by the response generation component deterministically, based on hand-crafted rules (McTear et al., 2016). Some research has been performed on developing more complex dialogue management capabilities based on reinforcement learning (Young et al., 2013), although these have not been implemented in practice as yet.

Types of Attacks via the Speech Interface Various possibilities for attacks via the speech interface have been identified. Bispham et al. (Bispham et al., 2018b) have developed a taxonomy of potential attacks via the speech interface which is organised according to the nature of the attack in terms of human perception. The taxonomy divides such attacks into two high-level categories; overt attacks, which aim to take control of a target system using plain-speech voice commands, and covert attacks, in which malicious voice commands are concealed in a cover medium so as to make them imperceptible to human listeners.

Overt attacks are easily detectable by users if they are consciously present with their device, therefore the success of an overt attack relies on a user being distracted or leaving their device unattended. An example of an overt attack is the activation of a smartphone by a voice command which is delivered via a malicious app whilst a user is away from their device (Diao et al., 2014). Covert attacks are by definition not detectable by users, and can therefore be executed even if the user is present with their device. Examples of covert attacks include high-frequency attacks which hide voice commands in sound which is inaudible to humans (Zhang et al., 2017), attacks which hide voice commands via an audio-mangling process which makes them appear to humans as meaningless noise (Carlini et al., 2016), and the targeted use of nonsensical word sounds which trigger target commands in a victim's system (Bispham et al., 2018a), despite these word sounds being perceived as meaningless by human listeners. Covert attacks are divided within the taxonomy into five sub-categories namely silence, noise, music, nonsense and 'missense', the hiding of malicious voice commands in speech which appears to be unrelated to the attacker's intent.

Overt attacks exploit the inherent vulnerability of speech interfaces on account of the difficulty of controlling access to such interfaces. Covert attacks exploit unintended functionality in the han-

dling of speech input by a voice-controlled system which allows it to accept input which is not a valid voice command. The 'silent' attacks demonstrated by Zhang et al. (Zhang et al., 2017) exploit nonlinearities in analog-to-digital conversion of speech signals by a microphone, whereas the attacks demonstrated by Carlini et al. (Carlini et al., 2016) and the attacks demonstrated by Bispham et al. (Bispham et al., 2018a) exploit vulnerabilities in speech recognition. Attacks targeting natural language understanding have not been demonstrated with respect to voice-controlled systems as yet, although there has been some related work on attacks on natural language understanding in other areas, for example in work on misleading question answering systems (Jia and Liang, 2017). As regards the dialogue management and response generation components, as these functionalities are fully dependent on input from the preceding components in the current generation of voice-controlled systems, there are no attacks targeting these functionalities at present.

Attack Scenarios An attacker's goal in executing an attack via a speech interface will be to gain control of one of the three generic types of action which can be performed via a voice-controlled digital assistant or other speech-controlled system using a sound-based attack. These three types of action are data extraction, data input and execution of a cyber-physical action. Specific attacks on each type of action which might be possible based on the current capabilities of voice-controlled digital assistants include, respectively, prompting disclosure of personal information such as calendar information (Diao et al., 2014), instigating a reputational attack by posting to social media in the victim's name (Young et al., 2016), and causing psychological or physical harm to the victim by controlling a device in their smart home environment (Dhanjani, 2015).

Attacks via a speech interface require a channel through which the sound-based attack is delivered, and in the case of attacks involving theft of information, successful execution also requires a channel for data exfiltration. Sound-based attacks might be delivered through various channels, including natural voice, radio or TV broadcasts or audio files which users might be induced to open via a weblink or email attachment (Dhanjani, 2015). Some researchers consider the injection of voice commands via a malicious smartphone app (Diao et al., 2014). A further possible attack delivery channel is via an intermediary device under the attacker's control. Some instances of compromise of internet-connected speakers have

been reported.² Speakers which have been compromised in this way could be used as an attack delivery channel for sound-based attacks on a target voice-controlled digital assistant within the speakers' vicinity. Regarding data exfiltration channels, Diao et al. (Diao et al., 2014) envisage for example that a system could be prompted to call a phone number linking to an audio recording device, which would then be used to record personal information of the victim which the system might be prompted to disclose by further voice commands.

Attacks via the speech interface have the potential to expand in time by perpetuating over a number of dialogue turns, as well as in space by spreading to other speech-controlled devices. Alepis and Patskakis (Alepis and Patsakis, 2017) and Petracca et al. (Petracca et al., 2015) both mention the possibility of attacks by voice 'spreading' from one device to another by hijacking of a device's speech synthesis functionality. An example of an attack via the speech interface spreading through both space and time was seen in an instance in which a Google Home device was prompted to provide data to its user in synthesised speech which was perceived by a nearby Amazon Echo device as a command. This prompted the Echo to provide data which was in turn perceived by the Google Home as a command, the consequence being to set in motion an 'endless loop between the two devices.'³ This instance represented an example of an 'attack' which spread both in space to another device as well as in time over a potentially endless number of dialogue turns. Whilst this particular instance represents merely a humorous anecdote, it is possible that more malicious actions might be performed using similar mechanisms.

Attack Modelling Techniques There are a number of techniques for attack modelling in cyber security. One of the more well-known modelling techniques

²See Wired, 27th December 2017, "Hackers can rickroll thousands of Sonos and Bose speakers over the internet", <https://www.wired.com/story/hackers-can-rickroll-sonos-bose-speakers-over-internet/> [accessed 29th August 2018] and Trend Micro report 2017, "The Sound of a Targeted Attack", <https://documents.trendmicro.com/assets/pdf/The-Sound-of-a-Targeted-Attack.pdf> [accessed 29th August 2018]

³See UPROXX, 12th January 2017 You Can Make Amazon Echo and Google Home Talk to Each Other Forever, <http://uproxx.com/technology/amazon-echo-google-home-infinity-loop/> [accessed 29th August 2018] and cnet.com 15th February 2018, "Make Siri, Alexa and Google Assistant talk in an infinite loop", <https://www.cnet.com/how-to/make-siri-alexa-and-google-assistant-talk-in-an-infinite-loop/> [accessed 29th August 2018]

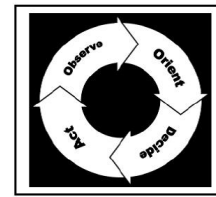


Figure 1: The four stages of the OODA Loop

for cyber security applications is the cyber kill-chain (Al-Mohannadi et al., 2016) which is used to analyse the different stages of malware attacks. Other established attack modelling techniques in cyber security include attack graphs (van Rensburg et al., 2016)) and attack grammars (Patten et al., 2016). Another type of attack model is the OODA loop. Originally developed for the military context (Boyd, 1996), the OODA loop has been applied in many different areas, including cyber defence (Klein et al., 2011). The OODA loop method represents the behaviour of agents in adversarial interactions as each continuously cycling through a four-stage loop in a shared environment, the four stages of the loop being observation (Observe), orientation (Orientation), decision (Decide) and action (Act). The four stages of the loop as presented by Klein (Klein et al., 2011) are shown in Figure 1. Rule (Rule, 2013) explains that the Observe and Act stages of the OODA loop are the points at which it makes contact with the external world, whereas the Orient and Decide stages are internal processes. Rule further explains that an adversary's aim as modelled by the OODA loop is to interfere with decision-making within their opponent's loop by presenting them with "ambiguous, deceptive or novel" situations, whilst at the same time continuing to execute their own loop independently.

3 ATTACK AND DEFENCE MODELLING

For the purposes of this work, the attack modelling technique considered to be the most suitable was the OODA loop. The reason for this was that the OODA model is capable of capturing the cyclical nature of human-computer interactions by speech. Therefore the OODA loop model is especially suitable for representing the ways in which the processes of human-computer interaction by speech may be hijacked by adversarial actions. Specifically, the capture of the speech signal by a microphone prior to speech and language processing can be mapped to the Observe stage of the OODA loop, the combined functionality of the automatic speech recognition and

natural language understanding components can be mapped to the Orient stage, the dialogue management (DM) component can be mapped to the Decide stage, and the response generation and speech synthesis stages can be mapped to the Act stage. Figure 2 shows a mapping of non-malicious user-device interactions via speech to the OODA loop model.

Figure 3 shows a mapping to the OODA loop model of the different types of attacks via the speech interface as categorised in the taxonomy presented by Bispham et al. (Bispham et al., 2018b), in which an attacker replaces a legitimate user in interactions with the device. The position of each type of attack in the loop model corresponds to the specific vulnerability exploited by the attack, i.e. the point at which the attacker gains control of the target device's loop. Plain-speech (overt) attacks and silent attacks are positioned at the Observe stage, as these types of attack exploit inherent vulnerability of the speech interface and unintended functionality in voice capture, respectively. All other types of attack (noise, music, nonsense and missense) are positioned at the Orient stage, as these types of attack exploit unintended functionality in speech and language processing. The attack model also shows an attack delivery channel for transmission of malicious input by sound, and a data exfiltration channel which is used if the aim of the attack is the extraction of data. The model further indicates the potential expansion of an attack in time over several dialogue turns, as well as the possible expansion in space to a second target. The attacker may be any agent which is capable of producing sound in an environment which it shares with a target. In the case of attacks involving extraction of data, the agent will also be capable of recording sound in the shared environment.

Figure 4 shows a mapping to the OODA loop model of currently available defence measures. The position of each defence measure in the loop corresponds to the type of system vulnerability which the defence measure aims to patch. Cyber security defence measures are often categorised as either preventive or reactive (Loukas et al., 2013). Preventive defence measures, such as authentication and access control, prevent malicious payloads from being inputted to a system at all, whereas reactive defence measures, such as anomaly-based or signature-based defences, detect that a malicious payload has been inputted and trigger a response to counteract the attack (Giraldo et al., 2017)). In terms of defence measures for human-computer interaction by speech as represented by the OODA loop model, preventive defences are defences which are applied prior to spoken language processing by the target system, i.e. at the Ob-

serve stage of the loop, whereas reactive defences are defences applied as part of spoken language processing, i.e. at the Orient stage of the loop. The preventive measures mapped to the Observe stage of the loop are user presence, access control, audio-technical measures, and voice authentication. Reactive measures mapped to the Orient stage are confidence thresholds, input validation, signature-based defences, and anomaly-based defences. As dialogue management and response generation are fully controlled by input from the preceding components in the current generation of voice-controlled systems, there is currently no scope for additional defences at the Decide stage of the loop.

User Presence Overt attacks via the speech interface using plain-speech voice commands are easily detectable by users if they are consciously present with their device. Whilst the ability to detect an overt attack may not prevent such attacks from being successful to some extent, as the attack may already be in the process of being executing as the user detects it, the immediate detection of an attack by a user clearly limits the potential effects of the attack, in that the attack is likely to be easily attributable, and the user will be able to prevent any further propagation of the attack. Therefore it is advisable for users to take preventative measures to ensure that overt attacks cannot be executed on their device whilst they are not present with it. Jackson and Orebaugh (Jackson and Orebaugh, 2018) recommend some basic preventative measures including unplugging a voice-controlled device when leaving the home and not placing a voice-controlled device close to doors and windows to prevent voice commands being inputted to the device from outside a house. User prevention measures such as these apply only to overt attacks and do not represent a defence against covert attacks which are imperceptible to humans and may therefore be executed notwithstanding the conscious presence of the user.

Access Control Some work has been done on the potential for using formal access control methods to secure interactions via a speech interface and other types of cyber-physical interactions. Agadakos et al. (Agadakos et al., 2017) use formal methods to develop a scheme for identifying unintended interactions which may be possible between devices in a smart home environment over 'hidden' physical channels, including voice. Petracca et al. (Petracca et al., 2015) propose a system of access controls to secure audio channels to and from a smartphone. The paper proposes an extension to the Android operation system in smartphones, with the objective of enforcing

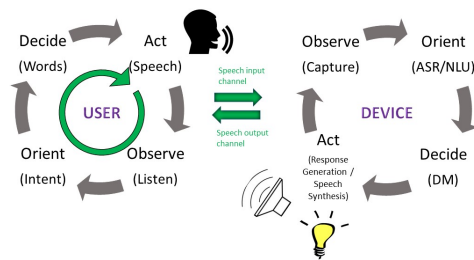


Figure 2: The OODA Loop in User-Device Interactions

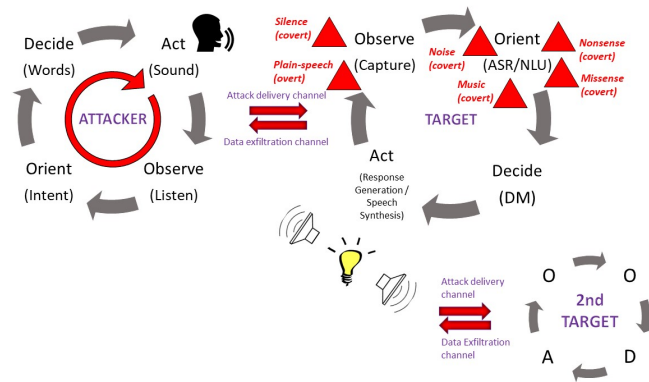


Figure 3: The OODA Loop in Attacker-Target Interactions

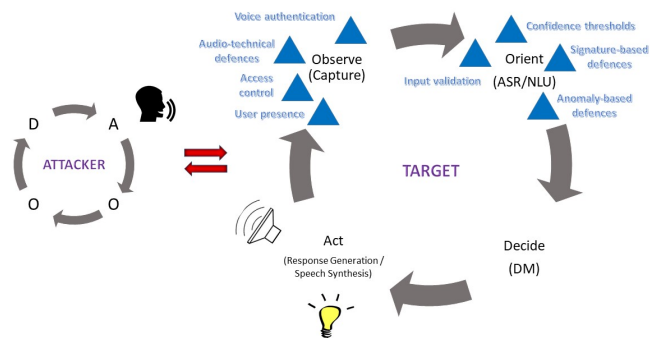


Figure 4: Defences against Attacks via the Speech Interface in the OODA Loop Model

security policies for communications over three audio channels, namely between the device's speakers and its microphone, between the device's speakers and external parties, and between external parties and the device's microphone. The authors concede that their access control system is based on the assumption of a reliable means of authenticating the legitimate user of a device, which may not be a valid assumption. Gong and Poellabauer (Gong and Poellabauer, 2018) argue that the 'Audroid' method developed by Petracca et al. is not effective against adversarial learning attacks.

Audio-Technical Defences Some defence measures have been presented which are applied at the voice capture stage of the handling of speech input by a voice-controlled device, prior the speech recognition and natural language understanding stages, so as to prevent 'silent' attacks which exploit non-linearity in microphone technology. As mentioned above, such attacks mislead a voice-controlled digital assistant or other voice-controlled device to execute commands which are concealed in high-frequency signals which are outside the human audible range, an example being the attack demonstrated by Zhang et al. (Zhang et al., 2017) mentioned above. Roy et al. (Roy et al., 2018) present a defence against inaudible attacks based on signal forensics which involves software rather than hardware changes to microphone technology. The applicability of such defence measures is limited to attacks which exploit vulnerabilities in the voice capture functionality of voice-controlled digital assistants; such measures are not effective against attacks which exploit vulnerabilities in the speech recognition or natural language processing functionalities.

Voice Authentication Biometric voice authentication, also known as speaker recognition, is perhaps the most obvious defence measure which might be implemented to prevent attacks on systems which are accessible via a speech interface. Hasan (Hasan et al., 2004) details how voice biometric authentication is performed using a standard set of acoustic features. In theory, voice biometrics represent a potential solution to all types of attack via the speech interface by ensuring that a speech-controlled device acts only on voice commands from an authorised user. In practice, however, voice biometrics remain vulnerable to spoofing attacks, as stated by Wu et al. (Wu et al., 2015). In an overview of the state-of-the-art in speaker recognition, Hansen and Hasan state that unlike in the case of other types of biometrics such as fingerprints, voice is subject to a certain amount of variability within the same individual as well between individuals, imply-

ing that some degree of potential for false positives in voice biometric authentication may be inevitable (Hansen and Hasan, 2015). The potential for false positives is exploited by attackers in voice spoofing attacks.

Confidence Thresholds Voice-controlled systems generally implement some form of confidence threshold to prevent them from accepting input which cannot be matched to one of their actions with sufficient certainty (Khan and Sarikaya, 2016). Whilst confidence thresholds are implemented as an error prevention measure rather than as a defence measure, they may have some defence functionality in preventing covert attacks via the speech interface, by enabling the system to reject malicious input which is not sufficiently similar to the examples of legitimate input which were used in training the system. However, a confidence threshold is unlikely to be sufficient to prevent all attacks. This was seen for example in the experimental work on nonsense attacks on Google Assistant described in Bispham et al. (Bispham et al., 2018a).

Input Validation Aside from confidence thresholds, another approach to error prevention for voice-controlled systems has been to restrict in some way the vocabulary which will be recognised by the system as valid input. Controlled Natural Language (CNL) has been used to prevent misunderstandings between machines and humans as to the intended meaning of natural language input. CNL is a general term for various restricted versions of natural language which have been constructed with a restricted vocabulary and syntax in order to enable every sentence in the language to be mapped unambiguously to a computer-executable representation of its meaning (Kuhn, 2014). Restricted language models like these have been developed particularly for contexts where avoiding misunderstandings is a critical concern, such as human-robot interactions in military applications (Ciesielski et al., 2017). Although primarily an error prevention rather than a security measure, CNL enables natural language input to be validated in the same way as other types of input to a system, as is often done for security purposes in non-speech interfaces (Schneider et al., 2015). Kaljurand and Alumäe (Kaljurand and Alumäe, 2012) discuss the use of CNL in speech interfaces for smartphones. They point to the additional challenges in using CNL in a speech-based application as opposed to a text-based application, noting the need to avoid homophones within the CNL which can be distinguished in written but not in spoken language. The approach proposed by

Kaljurand and Alumäe potentially addresses issues of confusability between user utterances which are within the intended scope of a speech-controlled system. However, they may not be effective in preventing confusion with out-of-vocabulary sounds which are directed to the system by a malicious actor. Thus CNL is unlikely to present a solution to preventing covert attacks which target the speech recognition functionality of a voice-controlled interface. Enforcement of a CNL in the design of a speech interface might also be effective in preventing missense attacks which exploit ambiguities in natural language input. However, such an approach would clearly be contrary to the aim of most providers of voice-controlled systems to enable users to communicate with their devices in as flexible and natural a way as possible (McShane et al., 2017).

Signature-based defences A potential defence against some types of attacks via the speech interface is detection of attacks based on detection of known attack signatures using supervised machine learning. Carlini et al. (Carlini et al., 2016), for example, propose a machine learning-based defence to their own covert audio-mangling attack, in the form of a machine learning classifier which distinguishes audio-mangled sentences from genuine commands based on acoustic features. They demonstrate that this classifier is effective against the specific attacks presented in their paper with 99.8 per cent detection rate of attacks. However, the authors themselves note that such defences do not represent a proof of security, and are vulnerable to ‘arms race’ with attackers who are likely simply to craft more sophisticated attacks to evade such defences. Attackers have the upper hand in such arms races with respect to machine learning based systems, on account of the vast number of possible inputs to such systems, making it impossible for defenders to prepare systems for all possible input in training.⁴

Anomaly-based defences One possibility for enabling voice-controlled systems to become resistant to previously unseen attacks via the speech interface could be defence measures based on some form of anomaly detection. Anomaly detection-based defences have been applied in other areas of cyber security, such as network defence (Rieck and Laskov, 2006), Bhuyan et al. (Bhuyan et al., 2014)). However, anomaly-based defence measures depend on re-

liable similarity and distance measures in terms of which malicious input can be distinguished as anomalous relative to legitimate input (Weller-Fahy et al., 2015). In the context of attacks via the speech interface, such quantifiably measurable indications of suspicious activity may be difficult to identify. Whilst a number of both phonetic and semantic distance measures have been developed (Pucher et al., 2007)(Gomaa and Fahmy, 2013), none of these are fully reliable in terms of their ability to separate sounds and meanings which are perceived as different by human listeners. Kong et al. (Kong et al., 2017) present the results of an evaluative study which indicated significant differences between error rates in human perception of speech sounds and their transcription by different types of automatic speech recognition in terms of a phonetic distance measure. Budanitsky and Hirst (Budanitsky and Hirst, 2001) compare different measures of semantic distance with implied human judgements of word meaning via a task which involved detection of synthetically generated malapropisms, finding that none of these measures were capable of alignment with human understanding of word meaning. Thus such distance and similarity measures do not provide a reliable basis for an anomaly detection-based defence against attacks which seek to exploit differences between human and machine perceptions of speech, and may also prevent the system from accepting legitimate input.

4 CONCLUSIONS AND FUTURE WORK

This paper presents a comprehensive overview of the security of the speech interface according to the OODA loop model, which has been used to model adversarial interactions in many contexts. The cyclical nature of the OODA loop model is especially well-suited to representing dialogue interactions and the ways in which these may be hijacked by malicious actors. The OODA loop is used as a framework for conceptualising attacks via the speech interface and for analysing the defence measures currently available to counteract them. Our analysis concludes that current defence measures are not adequate to prevent all types of attacks via the speech interface. Future work should consider the development of new types of defence measures to ensure security of speech interfaces. One possibility for future work might be to attempt to incorporate defence measures in the dialogue management component of voice-controlled systems, as represented by the Decide stage of the OODA loop.

⁴See Cleverhans blog, 15th February 2017, “Is attacking machine learning easier than defending it?”, <http://www.cleverhans.io/security/privacy/ml/2017/02/15/why-attacking-machine-learning-is-easier-than-defending-it.html> [accessed 29th August 2018]

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REFERENCES

Agadakos, I., Chen, C.-Y., Campanelli, M., Anantharaman, P., Hasan, M., Copos, B., Lepoint, T., Locasto, M., Ciocarlie, G. F., and Lindqvist, U. (2017). Jumping the air gap: Modeling cyber-physical attack paths in the internet-of-things.

Al-Mohannadi, H., Mirza, Q., Namanya, A., Awan, I., Cullen, A., and Disso, J. (2016). Cyber-attack modeling analysis techniques: An overview. In *Future Internet of Things and Cloud Workshops (FiCloudW)*, *IEEE International Conference on*, pages 69–76. IEEE.

Alepis, E. and Patsakis, C. (2017). Monkey says, monkey does: Security and privacy on voice assistants. *IEEE Access*.

Bhuyan, M. H., Bhattacharyya, D. K., and Kalita, J. K. (2014). Network anomaly detection: methods, systems and tools. *Ieee communications surveys & tutorials*, 16(1):303–336.

Bispham, M. K., Agraftiotis, I., and Goldsmith, M. (2018a). Nonsense attacks on google assistant. *arXiv preprint arXiv:1808.01947*.

Bispham, M. K., Agraftiotis, I., and Goldsmith, M. (2018b). A taxonomy of attacks via the speech interface. *pending publication in The Third International Conference on Cyber-Technologies and Cyber-Systems (CYBER 2018)*.

Boyd, J. R. (1996). The essence of winning and losing. *Unpublished lecture notes*, 12(23):123–125.

Brehmer, B. (2005). The dynamic ooda loop: Amalgamating boyds ooda loop and the dynamic decision loop.

Budanitsky, A. and Hirst, G. (2001). Semantic distance in wordnet: An experimental, application-oriented evaluation of five measures. In *Workshop on WordNet and other lexical resources*, volume 2, pages 2–2.

Carlini, N., Mishra, P., Vaidya, T., Zhang, Y., Sherr, M., Shields, C., Wagner, D., and Zhou, W. (2016). Hidden voice commands. In *25th USENIX Security Symposium (USENIX Security 16)*, Austin, TX.

Ciesielski, A., Yeh, B., Gorge, K., Basescu, M., and Tunstel, E. (2017). Vocal human-robot interaction inspired by battle management language. In *Systems, Man, and Cybernetics (SMC)*, *2017 IEEE International Conference on*, pages 3379–3384. IEEE.

Dhanjani, N. (2015). *Abusing the Internet of Things: Blackouts, Freakouts, and Stakeouts*. O'Reilly Media, Inc.

Diao, W., Liu, X., Zhou, Z., and Zhang, K. (2014). Your voice assistant is mine: How to abuse speakers to steal information and control your phone. In *Proceedings of the 4th ACM Workshop on Security and Privacy in Smartphones & Mobile Devices*, pages 63–74. ACM.

Giraldo, J., Sarkar, E., Cardenas, A. A., Maniatakos, M., and Kantarcioglu, M. (2017). Security and privacy in cyber-physical systems: A survey of surveys. *IEEE Design & Test*, 34(4):7–17.

Gomaa, W. H. and Fahmy, A. A. (2013). A survey of text similarity approaches. *International Journal of Computer Applications*, 68(13):13–18.

Gong, Y. and Poellabauer, C. (2018). An overview of vulnerabilities of voice controlled systems. *arXiv preprint arXiv:1803.09156*.

Hansen, J. H. and Hasan, T. (2015). Speaker recognition by machines and humans: A tutorial review. *IEEE Signal processing magazine*, 32(6):74–99.

Hasan, M. R., Jamil, M., Rahman, M., et al. (2004). Speaker identification using mel frequency cepstral coefficients. *variations*, 1(4).

Jackson, C. and Orebaugh, A. (2018). A study of security and privacy issues associated with the amazon echo. *International Journal of Internet of Things and Cyber-Assurance*, 1(1):91–100.

Jia, R. and Liang, P. (2017). Adversarial examples for evaluating reading comprehension systems. *arXiv preprint arXiv:1707.07328*.

Kaljurand, K. and Alumäe, T. (2012). Controlled natural language in speech recognition based user interfaces. In *International Workshop on Controlled Natural Language*, pages 79–94. Springer.

Khan, O. Z. and Sarikaya, R. (2016). Making personal digital assistants aware of what they do not know. In *INTER_SPEECH*, pages 1161–1165.

Klein, G., Tolle, J., and Martini, P. (2011). From detection to reaction-a holistic approach to cyber defense. In *Defense Science Research Conference and Expo (DSR)*, *2011*, pages 1–4. IEEE.

Kong, X., Choi, J.-Y., and Shattuck-Hufnagel, S. (2017). Evaluating automatic speech recognition systems in comparison with human perception results using distinctive feature measures. In *Acoustics, Speech and Signal Processing (ICASSP)*, *2017 IEEE International Conference on*, pages 5810–5814. IEEE.

Kuhn, T. (2014). A survey and classification of controlled natural languages. *Computational Linguistics*, 40(1):121–170.

Lison, P. and Meena, R. (2014). Spoken dialogue systems: the new frontier in human-computer interaction. *XRDS: Crossroads, The ACM Magazine for Students*, 21(1):46–51.

Loukas, G., Gan, D., and Vuong, T. (2013). A taxonomy of cyber attack and defence mechanisms for emergency management networks. In *Pervasive Computing and Communications Workshops (PERCOM Workshops)*, *2013 IEEE International Conference on*, pages 534–539. IEEE.

McShane, M., Blissett, K., and Nirenburg, I. (2017). Treating unexpected input in incremental semantic analysis. In *Proceedings of The Fifth Annual Conference on Advances in Cognitive Systems*. Palo Alto, CA: Cognitive Systems Foundation.

McTear, M., Callejas, Z., and Griol, D. (2016). *The conversational interface*. Springer.

Patten, T., Call, C., Mitchell, D., Taylor, J., and Lasser, S. (2016). Defining the malice space with natural language processing techniques. In *Cybersecurity Symposium (CYBERSEC)*, *2016*, pages 44–50. IEEE.

Petracca, G., Sun, Y., Jaeger, T., and Atamli, A. (2015). Audroid: Preventing attacks on audio channels in mobile devices. In *Proceedings of the 31st Annual Computer Security Applications Conference*, pages 181–190. ACM.

Pucher, M., Türk, A., Ajmera, J., and Fecher, N. (2007). Phonetic distance measures for speech recognition vocabulary and grammar optimization. In *3rd congress of the Alps Adria Acoustics Association*, pages 2–5.

Rieck, K. and Laskov, P. (2006). Detecting unknown network attacks using language models. In *International Conference on Detection of Intrusions and Malware, and Vulnerability Assessment*, pages 74–90. Springer.

Roy, N., Shen, S., Hassanieh, H., and Choudhury, R. R. (2018). Inaudible voice commands: The long-range attack and defense. In *15th USENIX Symposium on Networked Systems Design and Implementation NSDI 18*, pages 547–560. USENIX Association.

Rule, J. N. (2013). *A Symbiotic Relationship: The OODA Loop, Intuition, and Strategic Thought*. US Army War College.

Schneider, M. A., Wendland, M.-F., and Hoffmann, A. (2015). A negative input space complexity metric as selection criterion for fuzz testing. In *IFIP International Conference on Testing Software and Systems*, pages 257–262. Springer.

van Rensburg, A. J., Nurse, J. R., and Goldsmith, M. (2016). Attacker-parametrised attack graphs. *10th International Conference on Emerging Security Information, Systems and Technologies*.

Weller-Fahy, D. J., Borghetti, B. J., and Sodemann, A. A. (2015). A survey of distance and similarity measures used within network intrusion anomaly detection. *IEEE Communications Surveys & Tutorials*, 17(1):70–91.

Wu, Z., Evans, N., Kinnunen, T., Yamagishi, J., Alegre, F., and Li, H. (2015). Spoofing and countermeasures for speaker verification: a survey. *Speech Communication*, 66:130–153.

Young, P. J., Jin, J. H., Woo, S., and Lee, D. H. (2016). Badvoice: Soundless voice-control replay attack on modern smartphones. In *Ubiquitous and Future Networks (ICUFN)*, *2016 Eighth International Conference on*, pages 882–887. IEEE.

Young, S., Gašić, M., Thomson, B., and Williams, J. D. (2013). Pomdp-based statistical spoken dialog systems: A review. *Proceedings of the IEEE*, 101(5):1160–1179.

Zhang, G., Yan, C., Ji, X., Zhang, T., Zhang, T., and Xu, W. (2017). Dolphinattack: Inaudible voice commands. *arXiv preprint arXiv:1708.09537*.