CommanderSong: A Systematic Approach for Practical Adversarial Voice Recognition

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Abstract

ASR (automatic speech recognition) systems like Siri, Alexa, Google Voice or Cortana have become quite popular recently. One of the key techniques enabling the practical use of such systems in people’s daily life is deep learning. Though deep learning in computer vision is known to be vulnerable to adversarial perturbations, little is known whether such perturbations are still valid on the practical speech recognition. In this paper, we not only demonstrate such attacks can happen in reality, but also show that the attacks can be systematically conducted. To minimize users’ attention, we choose to embed the voice commands into a song, called CommandSong. In this way, the song carrying the command can spread through radio, TV or even any media player installed in the portable devices like smartphones, potentially impacting millions of users in long distance. In particular, we overcome two major challenges: minimizing the revision of a song in the process of embedding commands, and letting the CommandSong spread through the air without losing the voice “command”. Our evaluation demonstrates that we can craft random songs to “carry” any commands and the modify is extremely difficult to be noticed. Specifically, the practical CommandSongs over the air can achieve 94 percentage success rate.

1 Introduction

Intelligent voice control (IVC) has been widely deployed in human-computer interaction, such as Amazon Alexa \textsuperscript{[1]}, Google Now \textsuperscript{[4]}, Apple Siri \textsuperscript{[2]} and Microsoft Cortana \textsuperscript{[10]}. Thanks to speech recognition, the voice control system can interpret natural voice commands and execute the corresponding operations such as unlocking a home or car lock, making online purchases, sending messages, and etc. In this way, users only need to speak to an IVC device or application, which greatly improves their experience when interacting with the physical devices under certain circumstances (e.g., running, driving and etc.).

One of the key techniques enabling practical use of IVC in people’s daily life is machine learning, especially deep learning \textsuperscript{[22]}, which significantly increases the accuracy of speech recognition. Deep Learning Architecture, such as Deep Neural Network (DNN), has multiple hidden layers between the input and output layers \textsuperscript{[34]}. Theoretically, sufficient number of hidden layers can model any non-linear relationship \textsuperscript{[29]}, so as to distinguish very small differences between two voice samples. To build such complex models, a large amount of voice samples and special computing hardware are demanded in the training process.

However, deep learning is known to be vulnerable to adversarial perturbations \textsuperscript{[25, 13, 18, 15, 12, 36, 20, 32]}. Maliciously and even slightly crafted modification can cause DNN models to misbehave in an unexpected way. Although significant progress on adversarial learning has been made in the field of computer vision (i.e., adding adversarial perturbations to an image), little is known whether the adversarial perturbations are still valid on practical speech recognition. One main reason is that, in the field of computer vision, the raw inputs of the DNN are the pixels of an image. The computed digital adversarial perturbations can be interpreted as unnoticeable pixels, and then be easily integrated into the original (i.e., an image) to craft an adversarial sample (i.e., the revised image with the unnoticeable pixels). However, in the field of speech recognition, the adversarial perturbations directly added into the original voice typically cannot be recognized by the IVC devices.

To create a practical adversarial perturbation on given voices, we identified the following unique challenges. (1) The perturbation should not be filtered out by IVC devices. Since most IVC devices will remove background sound \textsuperscript{[38]} to increase the accuracy of recognition, the slight perturbation cannot be viewed as background noise. (2) The adversarial samples should work under physical
world environment where exists much more complicated impacts for the samples, e.g., electronic noise, etc. (3) The voice including targeted adversarial command should not be noticed by ordinary users. So the given voice should be carefully chosen so that the embedded command could attract less attentions from humans.

In this paper, we implement a practical and systematic adversarial attack on the real speech recognition systems. We choose a random song as the original audio based on its popularity, regardless of different desired commands that attackers would like to inject. We generate adversarial perturbations, which are generally considred to be inevitable noise generated by speakers, and embed them into the original song. We refer to such songs after embedding as CommanderSong, which misleads IVC devices to execute the corresponding operations after interpreting special commands from the songs. To make such CommanderSong, firstly, we randomly select a piece of song and generate a command audio by a text-to-speech (TTS) engine. Then we decode them separately by the open source toolkit Kaldi and extract the output of DNN. We manage to find what kinds of DNN output can be decoded as the target command. Taking it as the object, we carefully craft the song by gradient descent method to obtain the adversarial audio. Finally, considering environmental noise and speakers electronic noise when the adversarial audio is played over the air, we modify our gradient descent model to adapt to the practical attack scenario.

Contributions. The contributions of this paper are summarized as follows:

- **Physical world adversarial attack on automatic speech recognition systems.** We implement practical adversarial attacks to ensure the crafted audio can attack with the background noises and electronic noises of the devices. To the best of our knowledge, this is the first systematic approach to generate such practical attacks against DNN-based speech recognition system.

- **Long-distance attack on automatic speech recognition systems.** We leverage song as a command “carrier” to attack voice IVC devices, which can be broadcast through radio, TV, and any media player installed in portable devices like smartphone. To make the crafted song unnoticeable, we minimize the changes to the crafted songs. To the best of our knowledge, this is the first work that achieves such long-distance attack against DNN-based speech recognition systems.

Roadmap. The rest of the paper is organized as follows: Section 2 gives the background information of our study. Section 3 provides motivations and overviews on our approach. In Section 4, we elaborate the design and implementation. In Section 5, we present experimental results. Section 6 compares our work with prior studies and Section 7 concludes the paper.

2 Background

In this section, we first overview how existing speech recognition system works, and then introduce the details of the open source toolkit we use. Finally, we discuss the recent advance on attacks against both image and speech recognition systems.

2.1 Speech Recognition

Automatic speech recognition is a technique that allows machines to recognize/understand human acoustic signals. Besides the commercial products like Amazon Alexa, Google Now, Apple Siri, iFlytek, etc., there are also open-source resources such as Kaldi toolkit, Carnegie Mellon University’s Sphinx toolkit, HTK toolkit, etc. Figure 1 presents an overview of the typical speech recognition system, with two major components: feature extraction and decoding based on pre-trained models.

After the raw audio is amplified, filtered, and digitized, acoustic features need to be extracted from the processed audio signal. The features contained in the signal change over time, so short-time analysis is used to evaluate those features periodically. Common acoustic feature extraction algorithms include Mel-Frequency Cepstral Coefficients (MFCC), Linear Predictive Coefficient (LPC), Perceptual Linear Predictive (PLP), etc. Among them, MFCC is the most frequently used one in both open source toolkit and commercial products. Gaussian Mixture Models (GMM) can be used to analyze the property of the audio features. The extracted acoustic features are matched against pre-trained acoustic models to obtain the probability of phonemes. Hidden Markov Models (HMM) are generative models for statistical speech recognition. As GMM cannot describe a non-linear manifold of the data, people put forward to using Deep Neural Network-Hidden Markov Models (DNN-HMM) for speech recognition. It is widely used in academic and industry community since 2012.
Figure 2: Procedure of decoding by Kaldi.

way of beam searching the state transition path in HMM, the decoded text can be obtained. In other words, the language model is applied to produce the text by combining phonemes into words. Recently, end-to-end deep learning is used for speech recognition systems, which depend on scale datasets and uses CTC (Connectionist Temporal Classification) loss function to get the characters rather than phoneme sequence. DeepSpeech and Wav2Letter are popular open source end-to-end speech recognition systems [16, 33].

### 2.2 Kaldi Open Source Toolkit

Kaldi is one of the most popular open source toolkits for researchers. Its training and decoding algorithms use Weighted Finite State Transducers (WFSTs). The decoding graph HCLG is constructed as WFST, and the brief decoding procedure is shown in Figure 2. In detail, \( H \) contains the HMM definitions; \( C \) represents the context-dependency; \( L \) is the lexicon; \( G \) encodes the grammar or language model [9]. The final output is formatted as a lattice, a finite-state transducer which shows acoustic, language model, and transition weights. The state transition model in Kaldi records the transition probabilities and information about HMM topologies.

Transition identifiers (transition-ids) is put on the input labels of HCLG, besides, they are encoded with pdf identifiers (pdf-ids) and the output symbols represent the text. In detail, pdf-id is a number calculated by DNN/GMM, and it is used as an index to describe the probability density function (p.d.f.). An example of relationship between transition-id and pdf-id is shown in Table 1.

### 2.3 Existing Attacks against Image and Speech Recognition Systems

Nowadays people are enjoying the convenience of integrating image and speech as new input methods into mobile devices. Hence, the accuracy and dependability of image and speech recognition pose critical impact on the security of such devices. Intuitively, the adversaries can compromise the integrity of the training data if they have either physical or remote access to it. By either revising existing data or inserting extra data in the training dataset, the adversaries can certainly tamper the dependability of the trained models.

When adversaries do not have access to the training data, attacks are still possible. Recent research has been done to deceive image recognition systems into making wrong decision by slightly revising the input data. The fundamental idea is to construct an image that “looks” different from the views of human and machine. Depending on whether the adversary knows the algorithms and parameters used in the recognition systems, there exist white box and black box attacks. Note that the adversary always needs to be able to interact with the target system to observe corresponding output for any input, in both white and black box attacks. Early research [37, 35, 11] focuses on the revision and generation of the electronic image file, which is directly fed into the image recognition systems. The state-of-the-art research [25, 13, 18] advances in terms of practicality by printing the adversarial image and feeding it to image recognition systems.

However, the success on the attack against image recognition systems has not been ported to the speech recognition systems until recently due to the complexity of the latter. The speech, a time-domain continuous signal, contains much more features compared to the static images. Hidden voice command [14] launched both black box (i.e., inverse MFCC) and white box (i.e., gradient decent) attacks against speech recognition systems, and generated obfuscated commands to intelligent voice control systems. Though seminal in the speech recognition, it is also limited in the practical aspect. For instance, a large amount of human effort is involved as feedback for the black box approach, and the white box approach works on GMM-based acoustic models, which have been replaced by DNN-based ones in most modern speech recognition systems. The recent work DolphinAttack [39] proposed a completely inaudible voice attack by modulating commands on ultrasound carriers and leveraging the nonlinearity of the microphones. As noted by the authors, such attack can be eliminated by an enhanced microphone that can suppress acoustic signals on ultrasound carrier, like iPhone 6 Plus.

### 3 Overview

In this section, we present the motivation of our work, and overview the proposed approach to generate the practical adversarial attacks.

#### 3.1 Motivation

Recently, adversarial attacks on image classification have been extensively studied [13, 18]. Results show that even the state-of-the-art DNN-based classifier can be fooled by small perturbations added to the original image [25], giving erroneous classification results. However, the impact
of adversarial attacks on the most advanced speech recognition systems, such as those integrating DNN model, has never been systematically studied. Hence, in this paper, we investigated DNN-based speech recognition systems, and explored adversarial attacks against them.

Recent researches show that commands can be transmitted to IVC devices through inaudible ultrasonic sound [39] and noises [14]. Even though the existing works against ASR are seminal, they are limited in some aspects. Specifically, ultrasonic sound can be defended by using a low-pass filter (LPF) or analyzing the signal frequency range, and noises can be noticed by users. Therefore, our idea is to use songs, which are widely listened to. If the crafted song embedded with a command does not change too much, listeners will not notice the attack. Also, songs do not need to be played nearby. They can spread through radio, TV, or any media player installed in a smartphone, which enlarges the range of our attack. Hence, in our attack, we focus on (1) minimizing the impact of revising the song to embed the commands and (2) letting the CommanderSongs spread through the air regardless of the speakers.

### 3.2 Wav-to-API Attack

An ASR system is usually composed of two models: an acoustic model describing the relationship between audio signals and phonetic units and a language model representing statistical distributions over phonemes and words. We perform a white-box attack on the open source speech recognition toolkit, Kaldi [9], due to its popularity in research community. It is powerful including GMM-HMM, DNN-HMM and complex WFST decoding graph. Since the input of Kaldi is in the form of a wave file (in ‘wav’ format), we define the wav-to-API attack as crafting a song and ensure it can be decoded as a target command by Kaldi. To craft a CommanderSong, we test what kinds of pdf-ids can be decoded as a target command, and use gradient descent to add perturbations to the song audio, so that we manage to make the song as a command “carrier” with slight modification. We then feed the crafted song directly to Kaldi decoding system and evaluate the transcript results later. Since there does not exist any disturbance (i.e., environmental or electronic noises) over the translating process in this scenario, we only focus on Kaldi system itself and ignore the factor of other devices.

### 3.3 Wav-air-API Attack

For the practical attack, the adversarial audio should be played to interact with IVC devices over the air. Our wav-to-API attack above manages to craft a random audio which can be decoded as a certain command by Kaldi. In the physical world, however, we should ensure that the recorded wave of the played audio by a speaker can be decoded as the target command, and we take it as the wav-air-API attack. The challenge is that the electronic noises produced by the loudspeakers as well as the recorder, and the background noise in the open air have significant impacts on the recognizability of the crafted audio. Therefore, we improve our approach by adding noise influences to the gradient descent iteration algorithm. Then we play the crafted audio through three kinds of speakers and record the played audio separately over the air by an iPhone 6s smartphone. Finally, we evaluate our attack by comparing machine understanding and human comprehension about the recorded audio. The results show that both of the wav-to-API attack and wav-air-API attack can cheat the white-box Kaldi successfully, and be extremely difficult for human to recognize.

### 4 Attack Approach

Our idea to make a voice command unnoticeable is to integrate it in a song. In this way, when the crafted song is played, the ASR system will decode and execute the injected command inside, while users are still enjoying the
song as usual. As mentioned previously, two challenges should be addressed: (1) Minimizing the perturbations to the song, so the distortion between the original audio and the adversarial audio can be as much unnoticeable as possible, and (2) Making the attack practical, which means CommanderSong should be played over the air. To address the first challenge, our proposed approach is different from the previous approach that reverses the language model and the acoustic model together. Instead, we separate the language model (i.e., selection of pdf-ids) and design an algorithm to craft audio based on it. We try to find what kinds of DNN output can be decoded as the target text. Then we use gradient descent method to add minimum perturbations to the original audio to generate adversarial one. Finally, we overcome the second challenge by modeling both the environmental noise and the electronic noise to realize the physical attack. Below we elaborate the details.

### 4.1 Preparation

In order to use Kaldi to decode audio, it needs a trained model to begin with. There are some models on Kaldi website and can be used for research. Firstly, we took advantage of the “ASpiRE Chain Model” (referred as “ASpiRE model” in short), which is one of the latest released decoding models when we began our study. It is also the most popular version, since the source code on github obtains 3117 Star and 1527 Fork. After manually analyzing the source code of Kaldi (about 301636 shell script and 238107 C++ SLOC), we learned how Kaldi processes audio input and outputs speech texts. The whole process was shown in Figure 2 including the output of DNN, and the relationship between transition-id and pdf-id.

The original voice audio of the commands can be generated by any text-to-speech (TTS) engine (e.g., Google text-to-speech) or recording human voice, as long as generated by any text-to-speech (TTS) engine (e.g., Google text-to-speech) or recording human voice, as long as it can be correctly recognized by Kaldi platform. Finally, we randomly downloaded some songs from the Internet. To evaluate the effectiveness of using different types of songs as the carrier, we intended to choose songs from different categories, e.g., pop, rock, rap, and classical music.

### 4.2 Gradient Descent to Craft Audio

First we will describe the way that Kaldi decodes pdf-ids into texts and then introduce our approach to revise them to obtain the target commands. Basically, any word is composed of one or several phonemes, each of which is identified by transitions among several transition-ids. To illustrate the decoding procedure, we use Kaldi to process an audio with several words, and obtain the intermediate results, including the output matrix of DNN, the transition-ids sequence, the phonemes, and the decoded words. For example, the decoded file of “Echo” is shown in Figure 5. The red boxes mark values represented the phoneme-ids, and the state transition sequences are underlined, which indicate the transition relationship of HMM state for every phoneme. By looking up to the “Relationship between transition-id and pdf-id” table, we can obtain the pdf-ids sequence corresponding with the decode transition-ids sequence. A fragment of their relationship is shown in Table 1.

Figure 5 demonstrates the details of our attack approach. We use Kaldi to decode the song audio $x(t)$ and command audio $y(t)$ separately. By analyzing the decoding procedures, we can get the output of DNN matrix $A$ of the song audio (Step 1 in Figure 3) and the transition-ids sequence of the command audio (Step 2 in Figure 3). To modify $A$ into $A'$ that can be decoded as the command text, we first get the maximum values vector of it using Eq (1).

$$[V_m, a_m] = \max A_{M \times N}.$$  

where $V_m$ (m=1, 2, … M) is the maximum value vector of the $m_{th}$ frame (i.e., the $m_{th}$ row in matrix $A$), and $a_m$ is the corresponding pdf-id (i.e., the column in matrix $A$).

At Step 5 in Figure 3 we can get the pdf-id sequence of the command $b$. Using such pdf-id sequence as a reference, we can revise the original song audio until we construct a target DNN output $A'$ that can be decoded into the command text. Here we define our objective function to ensure that $a_m$ is same as $b_m$, where $a_m$ is the pdf-id vector of the maximum values computed from the DNN output matrix of $x'(t)$ (the crafted song audio) and $b_m$ is the decoded pdf-ids sequence of $y(t)$.

$$\arg\min |a_m - b_m|,$$

$$x'(t) = x(t) + \delta(t), |\delta(t)| \leq l.$$  

where $\arg\min$ signifies the minimum of the absolute value, $\delta(t)$ is the perturbation we introduced to the original song $x(t)$. Moreover, to preserve the fidelity of the original song, we set the revision limitation $l$ for $\delta(t)$.

Finally, we use gradient descent, an iterative optimization algorithm to find the local minimum of a function, to solve the objective function. Given an initial point, gradient descent follows the direction which reduces the value of the function most quickly. By repeating this process until the value starts to increase, the algorithm is able to find a local minimum value. In particular, based on our objective function, we revise the song $x(t)$ into $x'(t)$ with the aim of making the DNN output of $x'(t)$ be $A'$. 

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1There are three decoding models on Kaldi platform currently. ASpiRE Chain Model we used in this paper was released on October 15th, 2016, while SRE16 Xvector Model was released on October 4th, 2017, which was not available when we began our study. The CVTE Mandarin Model, released on June 21st 2017 was trained in Chinese.
Therefore, the crafted audio $x'(t)$ can be decoded as the desired command text.

To further preserve the fidelity of the original song, one method is to minimize the time duration of the revision. Typically, once the command audio is generated by a text-to-speech engine, all the phonemes are determined, so as to the transition-id sequence and $b$. However, the speech speed also determines the number of frames, and the number of transition-ids, for a phoneme. Intuitively, slow speech always produces repeated frames, or transition-ids, in a phoneme. Typically human needs six or more frames to realize a phoneme, but most speech recognition systems only need three to four frames to interpret a phoneme. Hence, to introduce the minimal revision to the original song, we can analyze $b_M$, reduce the number of repeated frames in each phoneme, and obtain a shorter $b'_Q, (Q < M)$.

### 4.3 Attack over the Air

Though feeding the audio file directly into Kaldi will let Kaldi decode the text desired by the attacker, playing the file through a speaker to physically attack an IVC device typically will not work. This is mainly due to the noises introduced by the speaker, environment and the receiver of the IVC device. We ignore the environmental noise due to the following reasons: (1) In a quite noisy environment, even the original voice command $y(t)$ may not be correctly recognized by IVC devices; (2) Modeling any slightly variant environmental noise is still an open research problem; (3) Based on our observation, in a normal environment like home, office, lobby, the major impact on the physical attack is the electronic noise from the speaker and the receiver. Hence, our idea to make the attack practical is to build the speech recognition model including the speaker and the receiver, and to attack the model using the previous approach.

To include the speaker and the receiver, we have to capture the noises introduced by them. Specifically, we carefully pick up several songs and played them through our speaker in a very quiet room. By comparing the recorded audio (captured by our receiver) with the original played one, we can capture the noises. Note that playing “silent” audio does not work since the electronic noise may depend on the sounds at different frequencies. Therefore, we intend to choose the songs that cover more frequencies. Regarding the comparison between two pieces of audio, we have to first manually align them and then subtract each value in the first WAV file from the second one. The result of subtraction is the captured noise. Finally, we intend to choose the songs that cover more frequencies.

Typically, once the command audio is generated by a text-to-speech engine, the attacker will not work. This is mainly due to the electronic noise from the speaker, environment and the receiver of the IVC device. We ignore the environmental noise due to the following reasons: (1) In a quite noisy environment, even the original voice command $y(t)$ may only work with the devices that the attacker uses to capture the noise. To “transfer” $x'(t)$ to other speakers and receivers, we introduce random noises. Specifically, based on the observation of the noises’ distribution, we randomly generate WAV files with the same distribution to simulate noises. Then we apply the generated random noises to Eq (3) as the new $n(t)$. Our evaluation results show that this approach can make the adversarial audio $x'(t)$ robust enough for different speakers and receivers. By taking the noise into account, we have generated the adversarial songs for practical attacks.

![Figure 5: Result of decoding “Echo”.](image)

Table 1: Relationship between transition-id and pdf-id.

| Phoneme | HMM-state | Pdf-id | Transition-id | Transition |
|---------|-----------|--------|---------------|------------|
| $eh_B$  | 0         | 6383   | 15985         | 0→1        |
|         |           |        | 15986         | 0→2        |
| $eh_B$  | 1         | 5760   | 16189         | self-loop  |
|         |           |        | 16190         | 1→2        |
| $k_I$   | 0         | 6673   | 31223         | 0→1        |
|         |           |        | 31224         | 0→2        |
| $k_I$   | 1         | 3787   | 31379         | self-loop  |
|         |           |        | 31380         | 1→2        |
| $ow_E$  | 0         | 5316   | 39643         | 0→1        |
|         |           |        | 9644          | 0→2        |
| $ow_E$  | 1         | 8335   | 39897         | self-loop  |
|         |           |        | 39898         | 1→2        |

$$\arg \min [a_M - b_M],$$
$$x'(t) + n(t) \rightarrow a_M,$$ (3)
$$x'(t) = x(t) + \mu(t), |\mu(t)| \leq l,$$

where $\mu(t)$ is the perturbation that we add to the audio, and $n(t)$ is the noise samples that we captured. In this way, we can get the adversarial audio $x'(t)$ that works over the air.

Since different speakers and receivers may introduce different noises when playing or receiving specific sound at a given frequency, $x'(t)$ may only work with the devices that the attacker uses to capture the noise. To “transfer” $x'(t)$ to other speakers and receivers, we introduce random noises. Specifically, based on the observation of the noises’ distribution, we randomly generate WAV files with the same distribution to simulate noises. Then we apply the generated random noises to Eq (3) as the new $n(t)$. Our evaluation results show that this approach can make the adversarial audio $x'(t)$ robust enough for different speakers and receivers. By taking the noise into account, we have generated the adversarial songs for practical attacks.
Table 2: Candidate songs to be crafted.

| Pop            | Rock         | Rap         | Classical  |
|----------------|--------------|-------------|------------|
| Good time      | Soaked       | Many men    | Love oath  |
| To my sky      | Gold         | Rap gold    | Lotus      |
| Love story     | Bang bang    | Get It On   | Castle in  |
|                |              | The Floor   | the sky    |
| Hello seattle  | When I see   | Marshall    | Heart      |
|                | you again    | matthers    | and soul   |
| A loaded smile | We are never | Selling     | Mariage    |
|                | ever getting | brick in    | amour      |
|                | back together| my street   |            |

5 Evaluation

We evaluated the effectiveness of CommanderSong in both wav-to-API attack and wav-air-API attack. We also evaluated the efficiency of CommanderSong generation.

5.1 Setting

We randomly downloaded 20 songs from Internet covering several categories such as pop, rock, rap, and classical music (five songs for each category). Regarding the commands to inject, we chose 10 commonly used ones such as “Okay google”, “turn on GPS”, “ask Capital One to make a credit card payment”. The commands are also in different length. Details of songs and commands are shown in Table 2. Though we performed detailed evaluation using the 10 commands and showed the results here, the results of other commands are similar.

For the practical wav-air-API attack that targets real IVC devices, we evaluated the results in a meeting room (16 by 8 meters, 4 meters tall). The songs were played and evaluated using three speakers (a JBL clip2 portable speaker, a TAKSTAR broadcast equipment and an ASUS laptop). All of them are commonly used in users’ daily life. The distance between the speaker and the IVC devices was 1.5 meters. Demos of attacks were uploaded on the website (https://sites.google.com/site/song2comdemo/).

5.2 Effectiveness

We evaluated the effectiveness of the two attacks: the first attack directly targets voice recognition APIs, suitable for those services that accept an audio file; the other attack played CommanderSong over the air, targeting real IVC devices in practical situation, which is never systematically achieved previously. We also tried to understand whether human users can identify commands inside the CommandSongs.

Wav-to-API Attack. In this attack, we used Kaldi [9] as the target, which is one of the most popular speech recognition system used around the world. We generated CommanderSongs using the 20 downloaded songs and the ten commands. Particularly, for each command, we injected it into the 20 songs. So we got 200 Commander-Songs for the ten commands in the end. These crafted songs were in the form of a wave file (in ‘wav’ format) and were sent to Kaldi. If Kaldi successfully identified the command injected inside, we say that the attack is successful.

Table 3 shows the results. The first column gives the ten commands (one command in a row). The second column shows the success rate $r_s$. Suppose for each command, the number of all command words is $n_c$ and the number of words that are successfully transcribed is $n_e$. Then $r_s$ is calculated by $n_e/n_c$. From the table, we found that $r_s$ is 100% for all the commands. That means, all the CommanderSongs can successfully attack Kaldi.

The third column demonstrates the human users reactions to the CommanderSongs. In this evaluation, 20 students from our university were involved. After letting them listen to each CommanderSong, we asked them whether they can identify commands in them. The third column is calculated as follows: $\sum_{n=1}^{m} n_{hs}/(n_{u} * n_{l})$. In the equation, $n_l$ is the number of commands; $n_{hs}$ shows the number of students who identified the commands inside. The ratio shows the average number of users who identified commands from the songs. From the table, none of them identified any commands. The reason is that CommanderSongs sound quite similar with the original song. For each command, we further calculated the average signal-noise ratio (SNR) of the 200 CommanderSongs (as shown in the fourth column). SNR is a parameter widely used to quantify the level of a signal power to noise in many areas. So we use it here to measure the distortion of the adversarial sample regarding the original audio. $SNR(dB) = 10\log_{10}(P(x)/P(\delta(x)))$. In the equation, the original audio $x(t)$ is the signal while the perturbation $\delta(t)$ is the noise. Larger SNR value indicates a smaller perturbation. From the table, the SNR ranges from 15~17dB, which is usually large enough to make sure that the CommanderSongs do not hear strange by human testers.

Wav-air-API Attack. Similar to evaluate the wav-to-API attack, we generated 20 CommanderSongs for each command. Then we played them over the air through three different speakers and use a receiver (an iPhone 6S) to record them, which are send to Kaldi to decode. If Kaldi successfully identified the command, we say that the attack is success. Table 4 shows the results. Similar to Table 3, the first column gives the commands to inject. The second column shows different speakers. The third column gives the success rates for the three speakers.
Table 3: Wav-to-API attack results.

| Commands                        | Success rate(%) | Identified commands (%) | SNR (dB) | Efficiency |
|---------------------------------|-----------------|-------------------------|----------|------------|
| Okay google restart phone now.  | 100             | 0                       | 18.6     | 229/1.3    |
| Okay google flashlight on.      | 100             | 0                       | 14.7     | 219/1.3    |
| Okay google read mail.          | 100             | 0                       | 15.5     | 217/1.5    |
| Okay google clear notification. | 100             | 0                       | 14       | 260/1.2    |
| Okay google airplane mode on.   | 100             | 0                       | 16.9     | 219/1.1    |
| Okay google turn on wireless hot spot. | 100 | 0                   | 14.7     | 280/1.6    |
| Okay google read last sms from boss. | 100 | 0                   | 15.1     | 323/1.4    |
| Echo open the front door.       | 100             | 0                       | 17.2     | 193/1.0    |
| Echo turn off the light, turn on the light. | 100 | 0                   | 17.3     | 347/1.5    |
| Echo ask capital one to make a credit card payment. | 100 | 0                   | 15.8     | 379/1.9    |

For JBL speaker, we found that 94% of the attacks were successful with $SNR = 1.7dB$. The fourth column shows None of human users can hear the commands inside of the CommanderSongs. That means, if an attacker performs the long-distance attacks to 1000 users in a city, around 940 of them would probably be attacked without their awareness. We also found that the success rate for the speaker JBL is the highest, which means that the quality of the speaker impacts the results of success.

5.3 Efficiency

To understand how efficient to generate a Commander-Song, for each command, we recorded the time to craft a CommanderSong using different songs. We describe the efficiency by showing the frames length of the command song and the time it cost to generate it. As shown in Table 3 and Table 4, efficiency is shown in the form as Frames/Time(hour). It can be seen that most of the CommanderSongs can be generated in less than 2 hours. That means, the attackers can generate the Commander-Song quickly. We also notice that the longer command does impact the time of generation greatly. A longer command commonly needs more time. However, some words (such as GPS and airplane) in the commands make the time longer. This may be because they are not commonly used in the training process of the “ASpIRE model”. To generate enough phonemes representing the words is not easy. Also, we found that, for some songs in type rock such as Bang bang and Roaked, the time to generate CommanderSong is longer. It seems that these songs are not stable, which may be the reason of long time. Knowing the time of generating CommanderSong could potentially help attackers to choose suitable songs as the commander “carriers”. Defenders may also pay more attentions to these types of songs since they may be more likely to contain commands.

6 Related Work

Prior to our work, there are plenty of researchers who have devoted to security issues about speech controllable systems [24, 17, 27, 39]. Kasmi et al. [24] stated that by leveraging intentional electromagnetic interference on headset cables, voice command could be injected and carried by FM signals which will be further received and interpreted by smart phones. Diao et al. [17] demonstrated through permission bypassing attack in Android smart phones, voice commands could be played using some applications with zero permissions. Mukhopadhyay et al. [27] considered voice impersonation attacks to contaminate a voice-based user authentication system. They reconstructed victims voice model from the victims voice data which could bypass authentication system. CommanderSong differs with these attacks that the songs embed with adversarial perturbations should not raise any special attentions by human users but IVC devices will misunderstand and then execute corresponding commands.

Much similar to our research, Zhang et al. [39] proposed DolphinAttack which is a completely imperceptible voice attack by leveraging modulation technology to generate commands on ultrasound carriers. Our work has two key differences. Firstly, our attack will not apply any other technology in order to hide the command, instead we focus more on feature extraction and deep learning processes. Secondly, as the authors stated, DolphinAttack can be obliterated by blinking away any acoustic signals with frequencies in ultrasound range, while our attack would not be influenced by the frequency filters. Carlini et al. used gradient descent generated adversarial noise samples to inject command for the GMM-HMM ASR system [14]. Recently, they posted the achievement that can construct targeted audio adversarial examples on DeepSpeech, which is an end-to-end open source ASR platform [28]. In the meantime, we are independently
doing the researches on DeepSpeech as well. Also, we achieve practical attacks that let the adversarial audio be played over the air while DeepSpeech relies on letting the speech recognition system directly receive the WAV files.

Besides attacking speech recognition systems, there has been substantial work on adversarial machine learning examples towards physical world. Kurakin et al. [25] proved it is doable that Inception v3 image classification neural network could be compromised by adversarial images. Brown et al. [13] showed by adding an universal patch to an image they could fool the image classifiers successfully. Evtimov et al. [18] proposed a general algorithm which can produces robust adversarial perturbations into images to overcome physical condition in the real world. They successfully fooled road sign classifiers to mis-classify real Stop Sign. However, our experiment significantly differ with the above since we mainly produce adversarial samples for speech recognition system.

7 Conclusion

In this paper, we perform practical adversary attacks on IVC devices by injecting “voice” commands into songs. Such CommanderSongs could let IVC devices execute any command while being played over the air without any notice by users. Based on CommanderSong, long distance attacks could be performed through radio, TV or media players. To the best of our knowledge, this is the first systematical approach to generate such practical attacks against DNN-based speech recognition system.

References

[1] Amazon Alexa. https://developer.amazon.com/alexa.
[2] Apple Siri. https://www.apple.com/ios/siri.
[3] CMUSphinx Open Source Speech Recognition. https://cmusphinx.github.io.
[4] Google Now. https://www.androidcentral.com/google-now.
[5] Google Text-to-speech. https://play.google.com/store/apps.
[6] HTK Speech Recognition Toolkit. http://htk.eng.cam.ac.uk/.
[7] iFlytek. http://www.iflytek.com/en/.
[8] kaldi-asp-kaldi. https://github.com/kaldi-asp-kaldi/tree/master/egs/aspire.
[9] Kaldi speech recognition toolkit. http://kaldi-asr.org.
[10] Microsoft Cortana. https://www.microsoft.com/en-us/windows/cortana.
[11] Wei Bao, Hong Li, Nan Li, and Wei Jiang. A liveness detection method for face recognition based on optical flow field. In Image Analysis and Signal Processing, 2009. IASP 2009. International Conference on, pages 233–236. IEEE, 2009.
[12] Battista Biggio, Igino Corona, Davide Maiorca, Blaine Nelson, Nedim Srdić, Pavel Laskov, Giorgio Giacinto, and Fabio Roli. Evasion attacks against machine learning at test time. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases, pages 387–402. Springer, 2013.
[13] Tom B Brown, Dandelion Mané, Aurko Roy, Martin Abadi, and Justin Gilmer. Adversarial patch. arXiv preprint arXiv:1712.09665, 2017.
[14] Nicholas Carlini, Pratyush Mishra, Tavish Vaidya, Yuankai Zhang, Micah Sherr, Clay Shields, David Wagner, and Wenchao Zhou. Hidden voice commands. In 25th USENIX Security Symposium (USENIX Security 16), Austin, TX, 2016.
[15] Nilesh Dalvi, Pedro Domingos, Sumit Sanghai, Deepak Verma, et al. Adversarial classification. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, pages 99–108. ACM, 2004.
[16] Rishita Anubhai et al. Dario Amodei, Sundaram Ananthnarayanan. Deep speech 2 : End-to-end speech recognition in english and mandarin. pages 1–10, 2016.
[17] Wenrui Diao, Xiangyu Liu, Zhe Zhou, and Kehuan Zhang. 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, 2014.
[18] Ivan Evtimov, Kevin Eykholt, Earlene Fernandes, Tadayoshi Kohno, Bo Li, Atul Prakash, Amir Rahmati, and Dawn Song. Robust physical-world attacks on deep learning models. arXiv preprint arXiv:1707.08945, 1, 2017.
[19] Dong Yu George Dahl Abdel-rahman Mohamed Navdeep Jaitly Andrew Senior Vincent Vanhoucke Patrick Nguyen Tara Sainath Geoffrey Hinton, Li Deng and Brian Kingsbury. Deep neural networks for acoustic modeling in speech recognition. DRAFT, 2012.
[20] Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572, 2014.
[21] Hynek Hermansky. Perceptual linear predictive (plp) analysis of speech. the Journal of the Acoustical Society of America, 87(4):1738–1752, 1990.
[22] Geoffrey Hinton, Li Deng, Dong Yu, George E Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N Sainath, et al. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. IEEE Signal Processing Magazine, 29(6):82–97, 2012.

[23] Fumitada Itakura. Line spectrum representation of linear predictor coefficients of speech signals. The Journal of the Acoustical Society of America, 57(S1):S35–S35, 1975.

[24] Chaouki Kasmi and Jose Lopes Esteves. "emi threats for information security: Remote command injection on modern smartphones". IEEE Transactions on Electromagnetic Compatibility, 57(6):1752–1755, 2015.

[25] Alexey Kurakin, Ian Goodfellow, and Samy Bengio. Adversarial examples in the physical world. arXiv preprint arXiv:1607.02533, 2016.

[26] LindaSalwa Muda, Mumtaj Begam, and Irraivan Elamvazuthi. Voice recognition algorithms using mel frequency cepstral coefficient (mfcc) and dynamic time warping (dtw) techniques. arXiv preprint arXiv:1003.4083, 2010.

[27] Dibya Mukhopadhyay, Maliheh Shirvanian, and Nitesh Saxena. All your voices are belong to us: Stealing voices to fool humans and machines. In European Symposium on Research in Computer Security, pages 599–621. Springer, 2015.

[28] David Wagner. Nicholas Carlini. Audio adversarial examples: Targeted attacks on speech-to-text. pages 1–7, 2018.

[29] Michael Nielsen. Neural Networks and Deep Learning. 2017. http://neuralnetworksanddeeplearning.com/.

[30] Douglas OShaughnessy. Automatic speech recognition: History, methods and challenges. Pattern Recognition, 41(10):2965–2979, 2008.

[31] Nicolas Papernot, Ian Goodfellow, Ryan Sheatsley, Reuben Feinman, and Patrick McDaniel. cleverhans v1.0.0: an adversarial machine learning library. arXiv preprint arXiv:1610.00768, 2016.

[32] Nicolas Papernot, Patrick McDaniel, and Ian Goodfellow. Transferability in machine learning: from phenomena to black-box attacks using adversarial samples. arXiv preprint arXiv:1605.07277, 2016.

[33] Christian Puhrsch Ronan Collobert and Gabriel Synnaeve. Wav2letter: an end-to-end convnet-based speech recognition system. pages 1–8, 2016.

[34] Jürgen Schmidhuber. Deep learning in neural networks: An overview. Neural networks, 61:85–117, 2015.

[35] Stephanie AC Schuckers. Spoofing and anti-spoofing measures. Information Security technical report, 7(4):56–62, 2002.

[36] Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus. Intriguing properties of neural networks. arXiv preprint arXiv:1312.6199, 2013.

[37] Roberto Tronci, Daniele Muntoni, Gianluca Fadda, Maurizio Pili, Nicola Sirena, Gabriele Murgia, Marco Ristori, Sardegna Ricerche, and Fabio Rolli. Fusion of multiple clues for photo-attack detection in face recognition systems. In Biometrics (IJCB), 2011 International Joint Conference on, pages 1–6. IEEE, 2011.

[38] Olli Viikki and Kari Laurila. Cepstral domain segmental feature vector normalization for noise robust speech recognition. Speech Communication, 25(1):133–147, 1998.

[39] Guoming Zhang, Chen Yan, Xiaoyu Ji, Tianchen Zhang, Taimin Zhang, and Wenyuan Xu. Dolphinattack: Inaudible voice commands. In Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security, pages 103–117. ACM, 2017.