Towards Weighted-Sampling Audio Adversarial Example Attack

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Abstract

Recent studies have highlighted audio adversarial examples as a ubiquitous threat to state-of-the-art automatic speech recognition systems. Nonetheless, the efficiency and robustness of existing works are not yet satisfactory due to the large search space of audio. In this paper, we introduce the first study of weighted-sampling audio adversarial examples, specifically focusing on the factor of the numbers and the positions of distortion to reduce the search space. Meanwhile, we propose a new attack scenario, audio injection attack, which offers some novel insights in the concealment of adversarial attack. Our experimental study shows that we can generate audio adversarial examples with low noise and high robustness at the minute level, compared to other hour-level state-of-the-art methods.

1 Introduction

In recent years, machine learning algorithms are widely used in various fields, and the security of the machine learning algorithm itself has attracted the attention of many researchers. Studies show that existing learning-based algorithms are vulnerable to adversarial attacks, e.g., adversarial examples [Szegedy et al. (2013); Goodfellow et al. (2014)]. Majority of the research on adversarial examples are in image recognition field [Carlini & Wagner (2017); Su et al. (2019); Liu et al. (2016); Chen et al. (2018); Evtimov et al. (2017); Kurakin et al. (2016), while others investigate fields such as text classification [Jia & Liang (2017), traffic classification [Liu et al. (2018)], malicious Software classification [Grosse et al. (2016); Hu & Tan (2017)] and so on.

Automatic speech recognition (ASR) is a vital field where machine learning algorithms are widely used [Hinton et al. (2012). For example, with the popularity of intelligent personal assistants such as Google Assistant, Amazon Alexa and Apple Siri, people can now use voice commands to conduct online shopping and control smart homes, cars, and more. If the attackers could silently replace the voice commands with audio adversarial examples, and fool the ASR while not being detected by a human listener, our security and privacy will be greatly threatened.

The good news is that in general it is much more difficult to generate adversarial examples for the audio inputs than for the image inputs. To generate an effective audio adversarial example, there are several technical challenges needed to be addressed:

(C1) The search space of generating an audio adversarial example is much larger than that of images. For example, the search space for audio sampled at 16KHz with a duration of 1 second is $10^4$ times larger than that of an image with $256 \times 256 \times 3$ pixels. It takes over one hour or more to generate an effective audio adversarial example by recently proposed approaches [Alzantot et al. (2018); Kreuk et al. (2018); Yuan et al. (2018)]. Such inefficiency makes the practicability of this attack very limited.

¹We encourage you to listen to these audio adversarial examples on this anonymous website: https://sites.google.com/view/audio-adversarial-examples/
Recording and replaying, which are common operations for audio, could easily introduce extra noise into audio. Therefore, the robustness of adversarial examples against noise is crucial. Nevertheless, the adversarial examples prepared over hours are still poor in robustness. The state-of-the-art audio adversarial examples [Carlini & Wagner (2018)] become invalid after adding $\pm 10$ pointwise random noise.

Existing audio adversarial examples may cause abnormal behaviors in natural ASR interactive environments. For example, when the victim’s greeting "How are you" is changed to an execution adversarial command, "open the front door". The victim will notice that something goes wrong with his Google Assistant as it fails to respond to his greeting. Instead, we could let Google Assistant not only silently execute the attack command but also respond to the victim’s greeting. We argue that the real, practical concealment of audio adversarial attack is crucial for interactive applications like ASR, while it is not yet well investigated by any of the prior studies.

In this work, we first propose two technologies named **Sampling Perturbation Technology (SPT)** and **Weighted Perturbation Technology (WPT)** to boost the efficiency and robustness of adversarial examples. By reducing the number of points to perturb based on the characteristics of context correlation in speech recognition model, our SPT can not only accelerate the generation speed (addressing C1), but also increases the robustness of adversarial examples against pointwise noise (addressing C2). The other method, WPT, works by adjusting the weights of distortion in different positions during the example generation process, our WPT can accelerate the convergence of the algorithm, and thus generate adversarial example faster and improve the attack efficiency (addressing C1). These two methods can always be composed together for better performance.

To best of our knowledge, we are the first to introduce the factor of the numbers and positions of perturbed points into the generation of audio adversarial examples. From this perspective, our approach is more general, and the existing methods, which are default to modify every value of the entire audio vector, are just special cases of our method. Experiments show that our standard attack, which is built on these two techniques, can generate more robust audio adversarial examples in 3 to 5 minutes. This is a substantial improvement compared to other state-of-the-art methods [Carlini & Wagner (2018); Yuan et al. (2018)].

We further propose a new attack scenario, **audio injection attack** which focuses on the concealment of the attack behavior (addressing C3). Inspired by SQL injection attacks [Halfond et al. (2006)], we don’t directly replace the original phrase with the targeted phrase, instead, we focus on the space character repeated at the beginning or end of the audio. We perturb these space characters to generate our secret message, i.e., our targeted phrase. Upon success, the adversarial example will be transcribed as the targeted phrase plus the original phrase. Such attack ensures that the original message will always get a proper response, while the real attack message can silently execute on the background.

The rest of the paper is organized as follows. Section 2 introduces the background of speech recognition and existing adversarial example attack on audio. Section 3 shows the analysis and implementation of our approach. In Section 4, we present and analyze the experimental results. Section 5 concludes the paper.

## 2 BACKGROUND

In this section, we briefly introduce core components of the state-of-the-art speech recognition systems and the existing methods of generating audio adversarial examples.

### 2.1 SPEECH RECOGNITION SYSTEMS

Before doing research about the audio adversarial example, we have to know about the core constructions of speech recognition systems and then choose a representative one to be our threat model. Audio files need to be aligned before being inputted into a learning-based model in the traditional method. Recently, most of the latest speech recognition systems adopt Connectionist Temporal Classification (CTC) method [Graves et al. (2006)] to avoid this alignment process. The input of CTC is an audio wave and the unaligned transcribed sentences. As for the system model, since voice information is often context-dependent, Hidden Markov Models (HMM) [Hinton et al. (2012)] or Recurrent Neural Networks (RNNs) like LSTM [Hochreiter & Schmidhuber (1997)] are often used.

Based on the above analysis, we choose the speech-to-text model Deepspeech [Hannun et al. (2014)] as our experimental threat model, which is the state-of-the-art open source model with CTC and LSTM as its core components. Moreover, our approach can be generalized to other models with these components.
2.2 AUDIO ADVERSARIAL EXAMPLES

After the threat model is selected, the general process of audio adversarial example attack is shown in Figure[1] Let $x$ be the input audio vector and $\delta$ be the slight distortion to the original audio. Similar to the definition of adversarial examples for images, audio adversarial examples mean that by adding some slight perturbation $\delta$, ASR recognizes $x + \delta$ as specified texts $t$, while there is no perceivable difference for humans. The process of generating adversarial examples is the process of updating $\delta$ by using gradient descent for some predefined loss function (minimize $l(x + \delta, t)$, where $l(\cdot)$ calculates how far away $x + \delta$ is transcribed from our target text $t$). This iterative process stops until the adversarial example meets our evaluation requirements. Here we give the evaluation metric in our experiments.

**Evaluation Metric.** We use $L_p$ distance to measure the distortion between two image vectors in most cases of image domain. In the field of audio, the loudness of audio vector $x$ is quantified by Decibels (dB):

$$dB(x) = \max_i (20 \cdot \log_{10}(x_i))$$

(1)

We calculate $dB_x(\delta)$ to measure the noise level of the distortion $\delta$ relative to the original audio $x$, so the larger $dB_x(\delta)$, the smaller distortion $\delta$:

$$dB_x(\delta) = dB(x) - dB(\delta)$$

(2)

We argue that the robustness of an adversarial examples attack should also be an important evaluation metric. Let $X_{adv}$ be the set of adversarial examples $x + \delta$. We evaluate the robustness of $X_{adv}$ to noise $\theta$ by the proportion of the valid adversarial examples after added pointwise random noise $\theta$:

$$R_\theta = \frac{1}{n} \sum_{i}^{n} valid(X_i + rand(-\theta, \theta))$$

(3)

Here, the validation means the adversarial example stays with its adversarial label.

In line with the focus of audio adversarial examples, we briefly introduce the existing methods of generating audio adversarial examples.

**Existing Methods.** Audio adversarial examples are generally divided into two categories, speech-to-label and speech-to-text [Yang et al., 2018]. Speech-to-label recognizes audio as a category and the output of such an ASR system is a specific label. This type of audio adversarial example can be generated by a similar method on images [Cisse et al., 2017; Alzantot et al., 2018]. Since the target of attack can only be selected from labels, this kind of attack is very limited.

Speech-to-text is to convert audio semantic information into text and output it. Audio adversarial example attack can let ASR transcribe any audio into a pre-specified text. [Carlini & Wagner] is the first to work on audio adversarial example generation for speech-to-text models and their generated examples are of good quality in terms of noise $dB_x(\delta)$. However, their robustness $R_\theta$ is not very good and most of their examples lose the adversarial labels when added noise $\theta$ is larger than 10. 10 is small enough to let original audio retain its classification. [Yuan et al.] proposed a method called WAV-AIR-API(WAA) to achieve practical adversarial attacks. [Yakura & Sakuma] realized another attack that can take effect in the real environment by simulating transformation caused by playback or recording and incorporating them in the generation process. Nevertheless, both of these two methods require over hours to generate an adversarial example. What’s more, the average $dB_x(\delta)$ of their adversarial examples is less than 20dB (Assuming that the original audio is between 60dB and 80 dB. When the noise $dB_x(\delta)$ is less than 20dB, it is already intolerable to human ears). **To the best of our knowledge, there is yet no method to generate audio adversarial examples with low noise and high robustness at the minute level.**

3 METHODOLOGY

In this section, we will first give the details of sampling perturbation technology and weighted perturbation technology. We will also explain why these methods are able to accelerate the attack and increase the robustness of adversarial examples. Then we give our standard adversarial attack to investigate the relationship between the numbers and positions of perturbed points, efficiency and robustness based on the ideas proposed before. Finally, we will introduce an attack scenario audio injection attack to show how to improve the concealment of attack.
3.1 SAMPLING PERTURBATION TECHNOLOGY

We propose SPT to accelerate the algorithm speed and increase the robustness of audio adversarial examples. It works by reducing the number of perturbed points. This method is inspired by the one pixel attack for images, which looks for adversarial examples with only one or several pixels changed [Su et al. 2019].

The reason why SPT works is related to the output of CTC. In CTC process (shown in Figure 2 left), we use \( x \) denote an audio vector and \( p \) denote a phrase. The process from \( x \) to \( p \) is: a) Input \( x \) (1) and get a sequence of tokens \( \pi \) (2). b) Then merge the repeated characters and drop '-' which means blank token (3). c) Output the predicted phrase \( p \) (4). The probability of output phrase \( p \) is defined as the product of probability \( y \) of each character in \( \pi \):

\[
P(p | y) = \sum_{\pi \in \prod(p, y)} \prod_{i} y_{\pi i}^{i},
\]

where \( \pi \in \prod(p, y) \) means \( \pi \) is the predicted sequence of phrase \( p \) with respect to probability \( y \).

In traditional audio adversarial example attack, if we want to transcribe phrase from \( p \) to target \( t \), we will give slight distortion on each \( \pi_i \) to let \( \max P(p | y') = t \). However, we can also get the same result \( P(p | y') = t \) by fixing part of \( \prod_{j} y_{\pi j}^{j} \), and perturbing the other part of \( \prod_{k} y_{\pi k}^{k} \):

\[
P(p | y') = \sum_{\pi' \in \prod(p, y')} \prod_{i} y_{\pi' i}^{i} \prod_{j} y_{\pi j}^{j} \prod_{k} y_{\pi k}^{k}
\]

Based on Formula 5, we can shorten the perturbed number of audio vector from \( n \) to \( m \). Our evaluations give the support that \( m \) can be much smaller than \( n \), for example, \( m = 5\% \cdot n \).

The reduction of the perturbed number of \( x \) brings two benefits to our adversarial examples:

1. It reduces the computation to make \( \max P(p | y') = t \) true, which accelerate the generation speed.
2. Since most of the points in our adversarial examples are exactly the same as those in the original audio (e.g. only 5 % of the points are different), this makes our adversarial examples show very similar properties to the original audio when facing pointwise noise.

3.2 WEIGHTED PERTURBATION TECHNOLOGY

WPT can accelerate the convergence of attack algorithm by adjusting the weights of distortion in different position. The improved loss function is the key part of WPT. We first introduce the loss function \( l(\cdot) \) that is commonly used in previous works [Taori et al. 2018; Carlini & Wagner 2018]. We then point out its limitations and give our solution.

\[
l(x, \delta, t) = ctc(x + \delta, t) + L_2(x, x + \delta)
\]
Formula $6$ gives the standard loss function, which we want to minimize during the adversarial example generation process. In particular, $ctc(x + \delta, t)$ the negative log likelihood of the adversarial example trial to our target phrase $t$. When $ctc(x + \delta, t) \leq 0$, it indicates $x + \delta$ is recognized as target $t$. In the words, the adversarial example $x + \delta$ could fool the recognition system. $L_2(\cdot)$ denotes the $L_2$ distance between the original audio vector $x$ and the adversarial example $x + \delta$. Smaller $L_2(\cdot)$ is desired, as it indicates that the adversarial example is less likely to be perceived by humans.

Decomposing $l(\cdot)$ into $l(\cdot) = L_{\text{target}} + L_{\text{input}}$, we found that the common loss function is mostly composed of two parts. The first part $L_{\text{target}}$ is to measure the difference between the current output of the model and the attack target. The second part $L_{\text{input}}$ is used to limit the difference between the adversarial examples and the original samples.

The decrease in traditional $L_{\text{target}}$ will make every aspect of the transcribed text more like the targeted text. That is, when we have already gotten the decoded "world" and our target is "world", what we need is to decode "a" to "o" rather than let "a" to be more "a"-like. Meanwhile, traditional $L_{\text{input}}$ is only measured by $L_2$ distance. No one has explored the influence of different $L_{\text{input}}$ on the convergence. We will improve the loss function from both $L_{\text{target}}$ and $L_{\text{input}}$.

**Exploration of $L_{\text{target}}$.** Find corresponding positions of the character "a" in the audio vector $x$ and perturb it preferentially can accelerate the convergence of attack algorithm. We mark the positions which need priority perturbed by increasing their weight.

**Audio Sequence Location (ASL)** is a model to help us decide which positions in the vector should have larger weights. As is shown in Figure 2(right), the inputs of ASL are current transcribed phrase $p'$ and target $t$ (1). After comparing $p'$ and $t$, we get the different characters (2). Find the positions of these characters in the sequence of tokens $\pi$ (3). Output the intervals $\chi^k$ in audio vector $x$ (4). Finally, the distortion corresponding to these $k$ positions in $\chi^k$ are multiplied by weight coefficients $\omega$. Therefore, our improved formulation of $L_{\text{target}}$ is:

$$L_{\text{target}} = \sum_{i}^{k} ctc(x_i + \omega_i \cdot \delta_i, \pi_i), i \in \chi^k$$  

(7)

There are two advantages of our improved $L_{\text{target}}$:

1. It’s effective against both a greedy decoder and beam-search decoder, which are two searching ways used in CTC. The reason is that instead of adjusting the weight of a single character or token, we adjust the weights of a continuous interval on the audio vector corresponding to the character. This distortion based on the continuous interval is effective for beam-search decoder.

2. We can use ASL at any time to get the key location intervals $\chi^k$ during gradient descent calculation. Then we make converge faster by adjusting the weight $\omega$ of $\delta$.

**Exploration of $L_{\text{input}}$.** Different from image data, audio has complicated format, which invokes a comprehensive study on the choices of $L_{\text{input}}$. In this work, we investigate four types of similarity measurement that are commonly used in the audio domain, as shown in Formula $8$.

$$
L_{\text{input}}^1 = c \cdot L_p(x, x + \delta) \\
L_{\text{input}}^2 = c \cdot (1 - \cos(x, x + \delta)) \\
L_{\text{input}}^3 = c \cdot L_p(\text{gram}(x), \text{gram}(x + \delta)) \\
L_{\text{input}}^4 = \frac{c}{dB_x(\delta)}
$$

(8)

In particular, $L_{\text{input}}^1$ and $L_{\text{input}}^2$ measures the $L_p$ distance and cosine distance between two audio vectors; $L_{\text{input}}^3$ gives the $L_p$ distance of spectrograms of two audios; $L_{\text{input}}^4$ denotes the dB degree of the distortion to the original audio.

A good choice of $L_{\text{input}}$ not only accurately reflect the auditory difference between the two audio frequencies but also avoid the optimization process oscillating around a solution without converging.

Since converting audio data into waveforms is not an equivalent conversion, that is, some information is lost after conversion. Based on this, we speculate that it has wider adaptability in the form of vector distance. However, other forms of measurement can be used as a complementary strategy for use in local optimization. We give a comparison of the effects of various loss functions in the experimental section.

5
3.3 IMPLEMENTATION AND SCENARIO

Here we give our standard adversarial attack and a new attack scenario audio injection attack shown in Figure 3 based on the technologies of § 3.2 and § 3.1. We focus on the factor of numbers and positions of perturbed points in this implementation. While audio injection attack is our new exploration of concealment of adversarial attack.

3.3.1 Our Standard Adversarial Attack

In this attack implementation, we want to transcribe audio into target phrase with fewer points, shorter time and smaller noise, and try to investigate the relationship among them. For example in Figure 3, someone said "how are you" and our method changed a few points of the audio vector. Finally, the ASR transcribed this perturbed audio into "open the door".

The specific steps to implement our attack is as follow:

1. Randomly select a certain proportion of points in $x$ and repeat gradient descent calculation on these points based on the normal loss function $l(\cdot)$ in Formula 6 (supported by § 3.1).
2. Calculate the Levenshtein Distance, which is a string metric for measuring the difference between two sequences, between the currently transcribed phrase $p'$ and the target phrase $t$.
3. When the Levenshtein Distance equals to 1, which means there is only one key character left from success, locate the corresponding positions of this character by ASL, and use our improved loss function in Formula 7 until we generate the effective adversarial example. (supported by § 3.2)

3.3.2 Audio Injection Attack

Audio injection attack focuses on the concealment of the attack behavior and is different from the traditional audio adversarial attack idea which completely replacing the original phrase with the targeted phrase.

To validate its feasibility, we tried to test the common intelligent personal assistants on the market. Take Google Assistant as an example, when we talk with it using the sentences in Table 1 respectively, the results show that Google Assistant successfully executed all the commands. This means when Google Assistant receives two commands at the same time, it can silently execute one command and reply to the other. Since this attack is similar to the SQL injection attack in which additional attack commands are added after the original SQL executes the command, we call this attack an audio injection attack.

Since one second of audio can transcribe up to 50 characters, theoretically audio injection attacks have enough space to inject in most of the audio. And the length of the modified part in this adversarial audio almost negligible compared to the entire length of the audio. Although we did not actually carry out a real attack on the Google Assistant, we hope...
Table 1: Commands and action records with Google Assistant.

| Command                                                   | Actions                                                                 |
|-----------------------------------------------------------|-------------------------------------------------------------------------|
| ok google play some music and hello world                 | a) My pixel started play music b) It answered "Now you’re speaking my language" |
| ok google airplane mode off and that’s cool               | a) My pixel turn off the airplane b) It answered "You got it"            |
| ok google read mail and I love you                        | a) My pixel listed my latest email b) It answered "That’s high praise coming from you" |

Table 2: Evaluation of our standard adversarial attack with Commander Song and C&W’s attack. (* As written in C&W’s paper: target phrase is chosen at random such that (a) the transcription is incorrect (b) it is theoretically possible to reach that target. )

| Attack Approach                      | Target phrase          | Proportion | Efficiency(s) | Prob | dB (δ) |
|--------------------------------------|------------------------|------------|---------------|------|--------|
| Our standard attack                  | hello world            | 30% points | 273           | 1    | 41.8   |
|                                      | echo open the front door | 30% points | 276           | 1    | 39.9   |
|                                      | okay google restart phone now | 30% points | 257           | 1    | 35.8   |
| Commander Song                       | echo open the front door | all points | 3600          | 1    | 17.2   |
|                                      | okay google restart phone now | all points | 4680          | 1    | 18.6   |
| C&W’s attack                         | Phrases chosen by C&W (*) | all points | ≈3600         | 1    | 31     |

that this approach will give researchers more inspiration, that is, it is very important to preserve the original semantic information in the audio, which can increase the concealment of the attack behavior.

The specific steps to implement audio injection attack is as follow:

1. Use ASL module to locate the blank region at the front of the original audio. For example, shown in Figure 3, the input of ASL are original sequence π and our target "OPEN THE DOOR AND " , then it will output all the locations of different characters. Finally, we only use the foremost or rearmost positions (first 3 in the example). (supported by §3.2)

2. Repeat gradient descent calculation on these points based on the normal loss function \( l(\cdot) \) in Formula 6 until get the adversarial example. (supported by §3.1)

4 EXPERIMENTAL RESULTS

In this section, we first show the evaluation of our standard adversarial attack. Our experimental results show that our approach has better efficiency, smaller noise, and stronger robustness than other attacks. We further evaluate different loss functions on success rate, dB and efficiency. In addition, we also study the performance of loss functions against the audio duration. Finally, we give our audio injection attack a feasible scheme. The experimental results support that our method can improve the concealment of adversarial attacks.

4.1 DATASET AND EXPERIMENTAL SETTINGS

Dataset. Mozilla Common Voice dataset (MCVD): MCVD is an open and publicly available dataset of voices that everyone can use to train speech-enabled applications. It consists of voice samples require at least 70GB of free disk space. We follow the convention in the field and use the first 100 test instances of this dataset to generate audio adversarial examples. Unless otherwise specified, all our experimental results are averaged over these 100 instances.

https://voice.mozilla.org/en/datasets
Environment. All experiments are carried out on an Ubuntu Server (16.04.1) with an Intel(R) Xeon(R) CPU E5-2603 @ 1.70GHz, 16G Memory and GTX 1080 Ti GPU.

4.2 EXPERIMENTS

4.2.1 Evaluating Adversarial Examples

In order to illustrate the effectiveness of our approach, we compared it with other two methods, Carlini & Wagner’s attack and CommanderSong et al. (2018).

Table 2 gives the success probability, average dB and efficiency for our method and two other state-of-the-art methods. For our method, we set $l_2 = L_{\text{input}}^2 + L_{\text{target}}$ as our loss function and the proportion of perturbed points is chosen to be 30%. Further discussion on their choices can be found in Section 4.2.4.

Our approach has better efficiency (more than $13 \times$ faster) than others. In addition, our adversarial examples also have better average dB, that is, we use less calculation time and get better results. Actually, our approach is more flexible, allowing attackers to choose to use more time or points to find smaller noise based on their needs. More importantly, our approach has better robustness which is shown in Section 4.2.2.

![Figure 4: Robustness comparison between our adversarial examples and C&W’s adversarial examples against pointwise noise.](image)

4.2.2 Evaluating Robustness to Pointwise Noise Defense

We respectively added pointwise noise to the original audio, our adversarial audio and Carlini & Wagner attack’s adversarial audio, transcribed the newly obtained audio, and then calculate $R_{\theta}$. If the newly transcribed phrase is the same as before, we say that this audio successfully bypassed a pointwise noise defense. Evaluation of Carlini & Wagner’s attack is obtained by using their open source code under our experimental environment. We tried our best to tune their methods for a fair comparison. The final results against pointwise noise from $\pm 5$ to $\pm 30$ are shown in Figure 4.

The curve of original audio can be used as a baseline. The robustness of Carlini & Wagner attack’s adversarial audio decreases rapidly with the increase of pointwise noise and the accuracy drops to 0 when noise reaches $\pm 25$. Our accuracy is very close to the baseline. An interesting phenomenon is that when noise is less than $\pm 10$, our robustness even exceeds the original audio. This is because the pointwise noise value added at this time is relatively small, which to a large extent just offsets the perturbation added when the adversarial example is generated, so that after adding the pointwise noise, our adversarial example is closer to the initial state than the original audio. Carlini & Wagner attack’s success rate drops rapidly after when noise is greater than $\pm 10$, which also shows the above reasons.

4.2.3 Audio Injection Attack

Assuming that the original semantic information of audio is $p$, we set the target phrase $t$ as "open the door and " (not including $p$). Our audio injection attack will attack each audio and make them transcribed as "open the door and " + $p$. Experimental results show that audio injection attack generated adversarial examples with a success rate of 85%. Most of their $dB_x(\theta)$ are greater than 40dB, which means the distortion is very slight and it almost unnoticeable to humans. Here we again suggest you listen to our demos on the website has given before.
In addition, considering the phonetic correlation of the context in the predicted sequence, we suggest that only the first 70% points in the injected part should be perturbed to avoid obvious influence on the following parts.

An interesting question is what if we directly set the target phrase as "open the door and " + p, instead of perturbing the beginning of the audio. Then we carried out the experiment with Carlini & Wagner’s approach.

In order to show the difference in results more clearly, we randomly select three adversarial examples and visualize their spectrograms in Figure 5. Compared with the spectrogram of the original audio, it can be clearly seen that the sample generated by our method has only slight distortion to the front part (red rectangular area), while C&W's attack has distortion almost on every point of the audio (black rectangular area).

We further notice that after the same number of iterations, the adversarial examples generated by C&W’s method often leads to context confusion, i.e., overlapping words or lost words. For example, when t is "it was dropping", the final adversarial example will be "open the donit was dropping". While our method can generate adversarial examples transcribed as t + p without confusion perfectly.

### 4.2.4 Evaluating Different Choices

In this experiment, we generate adversarial examples based on four different loss functions, from $l_1 = L_{input}^1 + L_{target}$ to $l_4 = L_{input}^4 + L_{target}$ (defined in Section 3.2). For each specific loss function, we conduct three adversarial attacks with the perturbation of 5%, 15% and 30% of the original audio respectively.

| Attack I: 5% | Attack II: 15% | Attack III: 30% |
|--------------|----------------|-----------------|
| loss         | Effic.(s) ↓    | Prob ↑          | $dB_z(\theta)$ ↑ | Effic.(s) ↓    | Prob ↑          | $dB_z(\theta)$ ↑ | Effic.(s) ↓    | Prob ↑          | $dB_z(\theta)$ ↑ |
| $l_1$        | 250.76         | 0.72            | 26.95            | 230.89         | 0.95            | 35.67           | 236.70         | 1               | 42.09           |
| $l_2$        | 292.98         | 0.75            | 27.41            | 257.39         | 1               | 36.01           | 273.30         | 1               | 42.49           |
| $l_3$        | 312.49         | 0.67            | 26.58            | 322.76         | 0.97            | 35.20           | 278.94         | 1               | 41.80           |
| $l_4$        | 243.68         | 0.64            | 26.88            | 217.82         | 0.94            | 34.79           | 273.77         | 0.99            | 39.85           |

The results in Table 3 suggests that $l_2$ has the best performance on success rate and $dB_z(\theta)$. Both $l_1$ and $l_2$ are calculated directly on the audio vectors. The superior performance of $l_2$ indicates that the characteristics of the cosine distance are more suitable for audio similarity measurement. Moreover, the changing of the amplitude of the sound wave is preferred compared to the change of its shape. The overall performance of $l_3$ is not satisfactory. We guess it is due to the information loss in the format conversion process, i.e., transforming the audio vector to a spectrogram. Since the size of $dB$ is related to the maximum value in the audio vector, it is impossible to measure the magnitude of the two small disturbances under the same maximum value, so the performance of $l_4$ is not as good as $l_2$, however, $l_4$ is good at time efficiency in most cases.

As for the perturbation ratio, when the ratio is small, the larger the ratio, the higher the success rate and the smaller the noise. However, if the ratio is large enough, the increase of the ratio will become redundant and lead to an increase in the search space, thus reducing efficiency. Therefore, we need to fine-tune the ratio to get the best efficiency, success rate, and noise.
We also studied the performance of different loss functions on efficiency and $dB\times(\theta)$ against the audio duration. Influenced by specific different audio context, each curve behaves differently at the same audio duration, however, from the average results in Figure 6 we can conclude that the audio duration and the efficiency are linearly increasing correlations. Because the longer the audio duration, the larger the search space, the correlation is reasonable. In addition, we also find the longer the audio duration, the better $dB\times(\theta)$. This shows that it is easier to convert audio into silence than other phrases.

5 CONCLUSION

This paper proposes the weighted-sampling audio adversarial example attack. Our experimental results show that our standard adversarial attack has better efficiency (more than $13\times$ faster), less noise, and stronger robustness. More importantly, we are the first to introduce the factor of the numbers and positions of perturbed points into the generation of audio adversarial examples. We also propose an audio injection attack scenario, which provides a new idea for how to increase the concealment of attack behavior. The study of the effectiveness of loss function shows there are some differences between the adversarial examples on image and audio. It also guides us on how to construct a more appropriate loss function in the future. Our future work will focus on the defense to audio adversarial examples.

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