TOWARDS MITIGATING AUDIO ADVERSARIAL EXAMPLES

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ABSTRACT

Audio adversarial examples targeting at automatic speech recognition systems have recently been made possible in different tasks, such as speech-to-text translation and speech classification. Here we aim to explore the robustness of these audio adversarial examples generated via various attack strategies by applying different signal processing methods to recover the original audio sequence. In addition, we also show that by inspecting the temporal consistency in speech signals, we can potentially identify audio adversarial examples considered in our experiments with promising success rate.

1 INTRODUCTION

Deep Neural Networks (DNNs) have been widely adopted in a variety of applications (Krizhevsky et al., 2012; Hinton et al., 2012; Levine et al., 2016). However, recent work has demonstrated that DNNs are vulnerable to adversarial perturbations (Szegedy et al., 2014; Goodfellow et al., 2015). An adversary can add negligible perturbations to inputs and generate adversarial examples to mislead DNNs, especially in image-based machine learning tasks (Goodfellow et al., 2015; Carlini & Wagner, 2017; Liu et al., 2017; Chen et al., 2017b;a)

Beyond images, given the wide application of DNN-based audio recognition systems, such as google home and Amazon Alexa, adversarial examples have also been studied recently (Carlini & Wagner, 2018; Alzantot et al., 2018; Cisse et al., 2017). In this paper, we aim to explore the robustness of such audio adversarial examples against different signal recovery methods. As a first attemp towards mitigating audio adversarial examples, we conduct extensive experiments to show that with different signal processing techniques, such as amplitude quantization, local smoothing, and down-sampling, the adversarial examples considered in our experiments can be recovered with high-quality recognition results without affecting the benign examples too much. In addition, we utilize the sequential dependency in audio data to discriminate audio adversarial examples, and find that based on temporal consistency checking, it is possible to identify audio adversarial examples. We perform the temporal consistency verification on both Libris (Nixdorf et al., 2010) and CommonVoice (Carlini & Wagner, 2018) datasets against the state-of-the-art attack method (Carlini & Wagner, 2017) considered in our experiments, and show that such approach can help achieve promising identification rate among the adversarial examples considered in this paper.

2 BACKGROUND ON AUDIO ADVERSARIAL EXAMPLES

Generally speaking, an adversarial example is an input x^a that is similar to a natural input x but will yield different output after passing through the neural network. Currently, there are two different types of audio adversarial attacks: Speech-to-label attack and Speech-to-text attack. Speech-to-label attack aims to find an adversarial example x^a close to the original audio x but yields a different (wrong) label. Moustafa Alzantot et al. proposed a genetic algorithm to generate such adversarial examples (Alzantot et al., 2018). In the targeted case, Speech-to-text attack requires the transcribed output of the adversarial audio to be the same as the desired output, which has been made possible by Carlini et el. using optimization-based techniques in (Carlini & Wagner, 2018).

3 METHODS TOWARDS MITIGATING ADVERSARIAL PERTURBATION

As a first attempt, we applied some primitive signal processing methods on audio data to recover them from adversarial noises without decreasing their quality too much. These methods are useful methods which are easy to implement, fast to operate and achieved some promising results.

- **Quantization:** By rounding the amplitude of audio sampled data into the nearest q-divisible integer number, the adversarial perturbation can be disrupted since its amplitude is usually small in the input space. We choose $q = 128, 256, 512, 1024$ as our parameters.
- **Local smoothing:** We use a sliding window of a fixed length for local smoothing to reduce the adversarial noises. For a sampled audio data x_i, we consider its k-nearest sampled data $x_{i-k+1}, x_{i-k}, \ldots, x_{i+k-1}$ as a local reference sequence and replace x_i by the smoothed value (average, median, etc) based on its reference sequence.
- **Down sampling:** Based on sampling theory, it is possible to down-sample an audio file without sacrificing the quality of the recovered signal while mitigating the adversarial noises in the reconstruction process. In our experiments, we down-sample the original 16kHZ audio data to using 8kHZ frequency and then perform signal recovery.

4 TEMPORAL CONSISTENCY BASED COMPARISON

Consider how an adversarial audio is generated: produce some unnoticeable noises on the origin audio elaborately to ensure every targeted phrase can be transcribed correctly. In another aspect, we argue that adversarial audio can be fragile since it needs complete audio information to resolve temporal dependency. If we cut the audio data into two parts, the natural audio data should be transcribed normally in each part despite of some phrases near the cut position. However, adversarial audio may not have this feature since the success of adversarial noises relies on the sequential nature of speech, rendering it inherently vulnerable to changes in temporal consistency of the input.

Consequently, we proposed a temporal-consistency-based approach to identify adversarial audios. Let x be the input audio and x^* be the first half part of x. Let $f(\cdot)$ denote the speech recognizing and transcribing process. To measure the similarity between $f(x)$ and $f(x^*)$ (they usually have different lengths), we only compare the prefix $f^*(x)$ of $f(x)$ that has the same length as $f(x^*)$ and ignore the rest. We use word error rate (WER), character error rate (CER) and longest common prefix ratio (LCP ratio) to evaluate the differences between $f^*(x)$ and $f(x^*)$. We will show that all of these metrics can effectively differentiate the adversarial examples and achieve high AUC scores.

5 EXPERIMENTAL RESULTS AND DISCUSSION

5.1 ANALYSIS FOR MITIGATING ADVERSARIAL PERTURBATION

In our experiments, we measure the robustness of audio adversarial attacks by Carlini et al. (Carlini & Wagner, 2018) and Moustafa Alzantot et al. (Alzantot et al., 2018). For Carlini's attack, we separately choose 50 audio files from two audio datasets (CommonVoice, Librispeech) and generate Carlini's attacks based on CTC-loss. We evaluate several signal processing methods based on WER and CER metrics and also report the ratio between the transcribing error rate referenced by ground

Table 1: Evalation on Commonvoice

Mitigation Methods	OriginWER(%)	OriginCER(%)	AdvWER(%)	AdvCER(%)
Without mitigation	37.7 (0.18)	18.5 (0.10)	95.8 (10.1)	83.0 (31.6)
Median-4	43.4 (0.21)	20.4 (0.11)	83.0 (0.46)	46.5 (0.34)
Downsample	47.2 (0.23)	23.3 (0.13)	77.6 (0.43)	43.9 (0.31)
Quantization-128	47.3 (0.24)	25.7 (0.15)	80.7 (0.52)	49.0 (0.40)
Quantization-256	52.5 (0.28)	29.2 (0.18)	73.4 (0.43)	43.6 (0.31)
Quantization-512	64.1 (0.35)	37.5 (0.24)	73.7 (0.43)	44.2 (0.31)
Quantization-1024	72.1 (0.42)	50.4 (0.37)	76.9 (0.45)	53.0 (0.41)

Table 2: Examples of the proposed attack mitigation approaches

Type	Decode results
Adv.	enough said the boy
Origin	they snuffed about the fur tree and rustled among the branches
Mitigated	they snuffed about the vertre and ruslled amon the branches
Origin	i would fe no if i am destined for so glorious a career cried the tree rejoicing
the first half of Origin	i would fe no if i am destined for so
Adv.	this is an adversarial example
the first half of Adv.	th is is an adverso

Table 3: AUC Results of Temporal Consistency Method

Dataset	LSTM	TC(WER)	TC(CER)	TC(LCP ratio)
Commonvoice	0.712	**0.936**	0.916	0.859
Librispeech	0.645	**0.911**	0.902	0.729

truth and the adversarial target (shown in brackets). Results are shown in Table 1 and 4. From the results we can see that most of our attack mitigation methods (e.g., Median-4, Downsample and Quantization-256) can effectively reduce the adversarial noises without affecting the origin audio's transcribed results too much. Table 2 are some attack examples disrupted by Quantization-256. The results are reasonable since they are merely some mistakes caused by similar phrase replacement or spelling errors. In order to further fix the transcribed results caused by reasonable mistakes, we used DeepSpeech's language model. The results are mentioned in Table 6, 7.

In Moustafa Alzantot's attack, we implemented their attack with 500 iterations and limit the magnitude of adversarial perturbation within 5, then we generated 50 adversarial examples on each attack task as shown in Figures 1, 2. The attack success rate is 84% on the labeled audio datasets, and the average unchanged label rate is 10.6%. For illustration, we use Quantization-256 as our mitigation method. The results against adversarial examples considered within our experiments are very promising, as can be observed in Figures 3, 4. The attack success rates decreased to only 2.1%, and 63.8% adversarial audio files are converted back to their original label. We also measure the possible effects on origin audio files caused by our mitigation methods: the origin audio without mitigation can be classified correctly with a rate 89.2%, and the rate decreased to 89.0% after applying our mitigation methods, which means the effects of our mitigation on benign instances are negligible.

5.2 Analysis for Temporal Consistency

Our temporal consistency analysis is based on Carlini's CTC-loss attack and used 100 randomly and separately picked audio files from CommonVoice and Librispeech audio datasets. Some inditified samples are shown in Table 2. As can be seen, while transcribing the sentence, the first half part of an natural audio changed a little comparing to the ground truth, but for the first part of adversarial audio, it changed a lot. Also, this method can be effective even the adversarial audio hides speech from being transcribed (i.e., silence): it revealed the underlying phrases.

We used three metrics including WER, CER, LCP ratio as mentioned before. Results from Table 9, 10 show the the corresponding differences between natural and adversarial audio files. We use these three metrics in our method and evaluate their performances by using AUC scores, together with a trained basel LSTM which has 64 hidden layer features as our baseline model. The comparison is presented in Table 3. We find that the single LSTM model's performance is not ideal, while using the WER metric achieved 0.936 on CommonVoice and 0.911 on Librispeech. The results suggest a simple but promising method for charactering adversarial audio attacks.

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6 APPENDIX

Table 4: Evalution on Librispeech

Mitigation Methods	OriginWER(%)	OriginCER(%)	AdvWER(%)	AdvCER(%)
Without mitigation	12.4 (0.07)	7.05 (0.06)	105.3 (65.8)	91.7 (611.3)
Median-4	16.4 (0.09)	8.0 (0.07)	57.9 (0.34)	27.5 (0.26)
Downsample	24.2 (0.13)	13.0 (0.11)	60.9 (0.35)	31.2 (0.28)
Quantization-128	13.4 (0.07)	7.6 (0.06)	66.1 (0.40)	37.1 (0.38)
Quantization-256	**16.3 (0.09)**	**8.9 (0.08)**	**48.6 (0.28)**	**24.0 (0.22)**
Quantization-512	27.5 (0.15)	13.8 (0.12)	47.0 (0.27)	23.0 (0.19)
Quantization-1024	46.8 (0.27)	25.4 (0.23)	52.3 (0.30)	30.0 (0.28)

Table 5: Mitigated Samples

Type	Mitigation results
Adv.	enough said the boy
Origin	they snuffed about the fur tree and rustled among the branches
Mitigated	they snuffed about the vertre and ruslled amon the branches
Origin	and he leaned against the wa lost in reveriey
Mitigated	and he leaned against the wall losting reavelete
Origin	and then what happens then
Mitigated	as the what happenis them

Table 6: Evalutation on Commonvoice with language model

Mitigation Methods	OriginWER(%)	OriginCER(%)	AdvWER(%)	AdvCER(%)
Without mitigation	27.5 (0.14)	14.3 (0.08)	95.9 (9.13)	80.1 (9.65)
Median-4	27.0 (0.14)	14.6 (0.08)	73.6 (0.59)	42.4 (0.29)
Downsample	31.2 (0.17)	17.6 (0.10)	69.6 (0.53)	41.2 (0.29)
Quant-128	34.4 (0.19)	21.3 (0.12)	75.9 (0.70)	45.3 (0.36)
Quant-256	42.9 (0.25)	26.7 (0.16)	70.7 (0.57)	41.8 (0.29)
Quant-512	52.4 (0.29)	37.1 (0.24)	68.5 (0.40)	45.0 (0.32)
Quant-1024	62.4 (0.36)	47.2 (0.35)	70 (0.41)	51.2 (0.39)

Table 7: Evalution on Librispeech with language model

Mitigation Methods	OriginWER(%)	OriginCER(%)	AdvWER(%)	AdvCER(%)
Without mitigation	3.05 (0.02)	1.46 (0.01)	102.8 (15.1)	86.5 (16.3)
Median-4	3.6 (0.02)	1.7 (0.01)	35.1 (0.23)	19.0 (0.17)
Downsample	11.8 (0.06)	5.7 (0.05)	41.2 (0.28)	21.8 (0.19)
Quant-128	3.2 (0.02)	1.5 (0.01)	49.7 (0.35)	28.2 (0.22)
Quant-256	**3.5 (0.02)**	**1.7 (0.01)**	**29.1 (0.18)**	**15.4 (0.13)**
Quant-512	12.0 (0.07)	6.6 (0.06)	25.1 (0.15)	13.3 (0.12)
Quant-1024	30.7 (0.19)	20.3 (0.18)	36.6 (0.23)	24.1 (0.22)

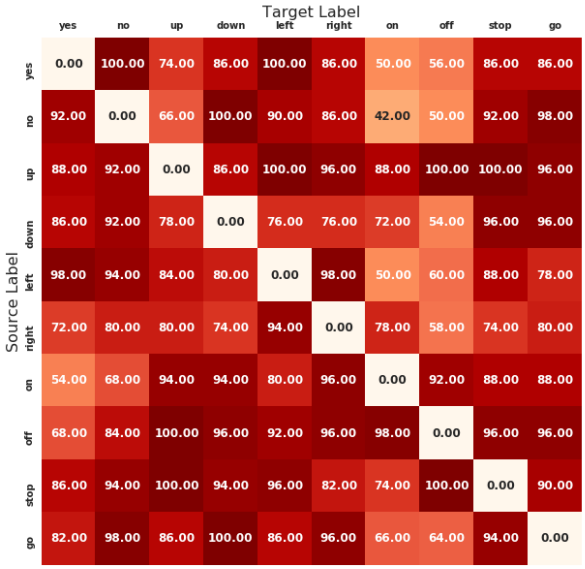

Figure 1: Successful attack rates

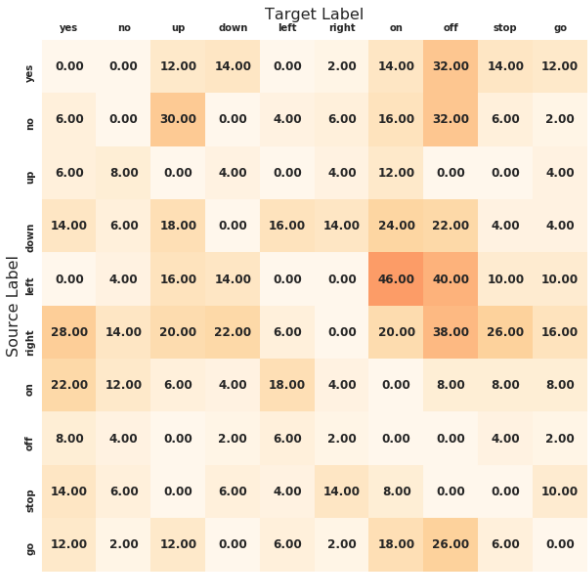

Figure 2: Unchanged label rates

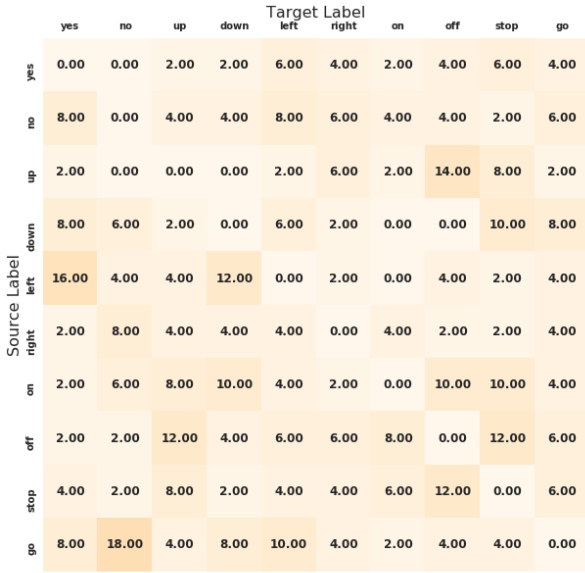

Figure 3: Successful attack rates after mitigation

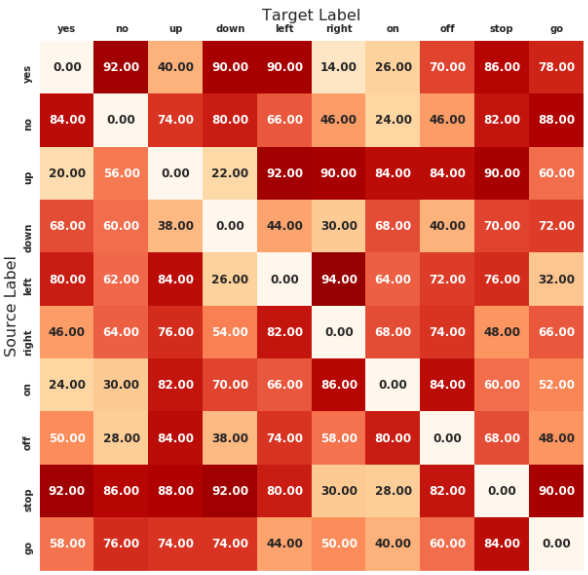

Figure 4: Unchanged label rates after mitigation

Table 8: Identified samples

Type	Decode results
Origin	i would fe no if i am destined for so glorious a career cried the tree rejoicing
the first half of Origin	i would fe no if i am destined for so
Adv.	this is an adversarial example
the first half of Adv.	th is is an adverso
Origin	have you not met them anywae
the first half of Origin	have you not
Adv.	*sil*
the first half of Adv.	have you not
Origin	this because you were not born
the first half of Origin	this because you were
Adv.	enough said the boy
the first half of Adv.	yens egasia or

Table 9: Identified results on Commonvoice

Metrics	Origin	Adversarial
WER(%)	37.4	96.0
CER(%)	16.2	61.1
LCP ratio(%)	27.3	2.08

Table 10: Identified results on Librispeech

Metrics	Origin	Adversarial
WER(%)	21.6	65.8
CER(%)	5.02	33.4
LCP ratio(%)	38.5	20.3