Detecting Audio Adversarial Examples with Logit Noising

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ABSTRACT

Automatic speech recognition (ASR) systems are vulnerable to audio adversarial examples that attempt to deceive ASR systems by adding perturbations to benign speech signals. Although an adversarial example and the original benign wave are indistinguishable to humans, theformer is transcribed as a malicious target sentence by ASR systems. Several methods have been proposed to generate audio adversarial examples and feed them directly into the ASR system (over-line). Furthermore, many researchers have demonstrated the feasibility of robust physical audio adversarial examples (over-air). To defend against the attacks, several studies have been proposed. However, deploying them in a real-world situation is difficult because of accuracy drop or time overhead.

In this paper, we propose a novel method to detect audio adversarial examples by adding noise to the logits before feeding them into the decoder of the ASR. We show that carefully selected noise can significantly impact the transcription results of the audio adversarial examples, whereas it has minimal impact on the transcription results of benign audio waves. Based on this characteristic, we detect audio adversarial examples by comparing the transcription altered by logit noising with its original transcription. The proposed method can be easily applied to ASR systems without any structural changes or additional training. The experimental results show that the proposed method is robust to over-line audio adversarial examples as well as over-air audio adversarial examples compared with state-of-the-art detection methods.

CCS CONCEPTS

• Security and privacy; • Computing methodologies → Speech recognition;

KEYWORDS

automatic speech recognition system, audio adversarial examples, logits, adversarial example detection, over-line & over-air attack

1 INTRODUCTION

With the development of deep learning techniques, automatic speech recognition (ASR) systems have been developed rapidly. Owing to the development of ASR systems, intelligent voice assistants (IVA), such as Google Assistant [13], Amazon Alexa [5], Apple Siri [6], and Microsoft Cortana [23] are widely used in human-machine interfaces. Through voice command, people can get their smartphones or smart speakers to schedule their personal appointments, open doors, and send text messages.

However, ASR systems are vulnerable to audio adversarial examples [3], which are malicious audio signals made by adding small perturbations to benign speech signals to fool deep neural networks (DNNs). Humans cannot distinguish these examples from the original contents of the speech, although the signals are slightly noisy. However, they are recognized as malicious content by ASR systems (Figure 1). Many researchers have proposed methods to generate adversarial examples to attack DNN-based ASR systems [15, 26, 31]. Most generated adversarial examples are directly fed into the ASR system over the line [8, 21, 30, 32, 34]. Furthermore, researchers have demonstrated the feasibility of attacking ASR systems using over-air adversarial audio signals known as physical audio adversarial examples [9, 10, 27, 29, 34, 36], which are made by considering real environmental audio noises when the audio signals are played over the air. These attacks can pose a severe risk to IVAs and control systems. For example, an attacker can conceal an attack command in a piece of music or a voice message on the radio, either to get money sent to a specific account or to keep the navigation in search of the wrong location.

Several researchers have proposed methods to defend against the attacks. A line of work has tried to train a robust ASR model [11, 19, 33]; however, these methods suffer a significant accuracy drop [3, 10]. Meanwhile, methods to detect adversarial examples have been proposed. Kwon et al. [16] proposed a detection method using audio preprocessing such as low-pass filters or high-pass filters,
and Zhuolin et al. [35] proposed a detection method using audio splitting. Although these methods seem to be effective for over-line audio adversarial examples, these research did not consider over-air audio adversarial examples. Recently, a new method based on signal reverberations [12] was proposed to detect robust physical audio adversarial examples. However, this method requires multiple wave inferences to evaluate whether the input wave is an audio adversarial example or not; therefore, it has a large time overhead.

In this paper, we propose logit noising, a novel method to detect an audio adversarial example. We add noise to logits, which is the output of an acoustic model in ASR system (Figure 2). The method is based on the observation that the logits of benign audio waves and audio adversarial examples have different distributions. Therefore, the transcriptions of benign audio waves are rarely changed following logit noising, whereas those of adversarial examples are easily altered. We then distinguish adversarial examples from benign waves by comparing the extent of transcription distortions arising from logit noising. Through extensive experiments, we show that the proposed method can achieve 100% detection accuracy on over-line audio adversarial examples and over 95.0% accuracy on over-air attacks. The proposed method is easily applicable to existing trained models because it requires no structural change or no additional training procedure. Moreover, as the method requires no additional inference for an input, it reduces the time overhead compared with state-of-the-art detection methods [12, 16, 35].

Our main contributions are as follows:

- We show that logits of benign audio waves and adversarial examples have different characteristics. We then conduct an analysis to determine the threshold for distinguishing adversarial examples.
- We propose logit noising, a novel method to detect audio adversarial examples by adding noise to the intermediate results (logits) of ASR systems. We demonstrate that the proposed method can effectively detect both over-air and over-line adversarial examples.
- We show that the proposed method can be easily deployed in real-world ASR systems because of its high compatibility (no structural change or retraining) and high efficiency (less overhead).

The remainder of this paper is organized as follows. In Section 2, we present background information on ASR systems. In Section 3, we present the related research on audio adversarial attacks and defense methods. The proposed detection method and experimental evaluation results are presented in Section 4 and 5, respectively. In Section 6, we provide the discussion. In Section 7, we provide our conclusions.

2 BACKGROUND: AUTOMATIC SPEECH RECOGNITION

ASR is a process in which a system interprets human speech and converts the content into text data. In this work, we experiment on the open-source DNN-based ASR framework DeepSpeech [15], which has been the target of many audio adversarial examples [8, 9, 21, 34], to demonstrate our proposed method. Figure 2 is an overview of this system. The ASR architecture consists of three major components for audio transcription, namely, feature extraction, model inference, and decoding.

**Feature extraction.** In this phase, the input wave is converted to a mel-frequency cepstrum coefficient (MFCC) [24] based on human hearing perceptions. First, the input wave is split into short time frames (20 ~ 40 ms) with overlapping. For each frame, a fast Fourier transform [28] is used to generate the frequency domain data. However, the linearly spaced result cannot characterize human perception effectively because humans perceive frequency non-linearly. To approximate the human perception, the frequency domain data are converted to mel-scaled data using mel-filter. Subsequently, MFCC feature vectors are obtained by taking the discrete cosine transform [4] of the log of mel-scaled data.

**Model inference.** The extracted MFCC features are passed to a DNN acoustic model. The target system uses a recurrent neural network (RNN) as the DNN acoustic model. Generally, an RNN-based acoustic model accepts a variable-sized MFCC vector as input. The acoustic model then outputs the sequence of character likelihood. In this paper, we call one character likelihood as logits (Figure 2: Model Inference).

**Decoding.** The logits sequence is transcribed to character-level transcription using beam-search decoding. The beam-search decoding functions by taking the logits and looking for the most likely text sequence according to the logits sequence. Finally, the character-level transcription is passed through a language model to
be properly transcribed. The language model outputs the final transcription based on word and semantic proximity using the N-gram model.

3 RELATED WORK

3.1 Adversarial Attacks in ASR

Adversarial examples are maliciously crafted audio waves that are intended to cause mistranscriptions by the ASR systems [8, 34, 36]. Most attacks are aimed at producing the targeted malicious sentences; they are a severe security threat [9, 20]. For example, an attacker may open a door by submitting adversarial examples that are perceived as “hello world” to the human hearing system (Figure 1).

To generate such examples, an attacker is required to possess a certain knowledge of the target ASR system. A white-box attack is developed under the assumption that an attacker has full knowledge of the target ASR system including the DNN structure, trained parameters, and preprocessing method. The attacker then generates an example by adjusting the example using gradients through the full ASR process. A white-box attack is the best scenario for an attacker, as it can generate the most powerful adversarial examples.

A black-box attack is developed under the assumption that an attacker cannot access the internal parameters of the ASR system. Therefore, the attacker must generate an adversarial example using only the transcription result from the target system.

In this study, we aim to detect two types of audio adversarial attacks: over-line and over-air attacks. The first is a type of attack that assumes the generated adversarial audio wave is directly passed to the ASR system (Figure 3a). Then, the adversarial wave is mistranscribed by the ASR system without any interference. On the other hand, in an over-air attack (Figure 3b), it is assumed that the adversarial audio wave is aired through the speaker to the target ASR system. During recording, the wave is affected by ambient noise, the room environment, and the capability of the recording device. Therefore, over-air attacks are designed to maintain the adversarial effect on waves in different environments. We provide detailed examples of both types of attacks below.

3.1.1 Over-line attack.

C&W. [8] Carlini & Wanger proposed a white-box targeted attack. The authors showed that any source audio can be mistranslated to any attacker’s intended phrase through small perturbation. In this attack, an attacker selects a target phrase and uses a connectionist temporal classification (CTC) loss [14] function as an objective function. The CTC-loss sums up the probability of possible alignments of input to target, producing a loss value which is differentiable with respect to each input. From this, an attacker can continually update audio adversarial examples through gradient-descent.

\[
\text{argmin} \, dB_x(\delta) + c \cdot L_{\text{ctc}}(\text{ASR}(x + \delta), t)
\]

where \(t\) is the target phrase and \(c\) is the importance of the adversarial part. An attacker can achieve a human-imperceptible but machine-effective adversarial perturbation by optimizing this equation.

Taori. [32] Taori et al. proposed a black-box attack. They introduced a momentum mutation inspired by the momentum update for gradient descent. With momentum update, the mutation probability changes according to the following exponentially weighted moving average update:

\[
\mathcal{P}_{\text{new}} = \alpha \cdot \mathcal{P}_{\text{old}} + \frac{\beta \cdot \mathcal{S}_{\text{core}}}{\mathcal{S}_{\text{core}} - \mathcal{S}_{\text{core}}}
\]

where \(\mathcal{S}_{\text{core}}\) is CTC-loss. For each iteration, they computed the \(\mathcal{S}_{\text{core}}\) and updated the new mutation probability, thereby creating optimal audio adversarial examples.

3.1.2 Over-air attack.

Hiromu. [34] Hiromu et al. presented an advanced white-box targeted adversarial attack. They investigated the feasibility of attacks using audio adversarial examples in the physical world, that is, attacks whereby a speaker makes a sound over the air and a microphone receives it. To generate over-air audio adversarial examples, the authors suggested the optimization using expectation over transformation (EoT) [7]:

\[
\text{argmin} \, \mathcal{E}_{\mathcal{H}}[dB_x(\delta) + c \cdot L_{\text{ctc}}(\text{ASR}(x' + \delta), t)]
\]

where \(x' = \text{Conv}_\mathcal{H}(x + \text{BPF}_{1000-4000Hz}(\delta))\). \(\text{BPF}\) means band-pass filter, \(\text{Conv}\) means convolution, and \(\mathcal{H}\) represents a set of collected impulse responses. They showed the feasibility of such attacks considering various reverberations and ambient noises.

In general, over-air attacks are more robust than over-line attacks because they are generated based on various external factors such as background noise and device internal noise.

3.2 Detection Methods

Defenses against audio adversarial examples have been extensively researched. To create a robust speech recognition system, many researchers have adopted adversarial training techniques [11, 19, 33], which have achieved excellent performance in image classification.
Audio random filter. Kwon et al. [16] proposed input audio modification using random filters such as high-pass, low-pass, or notch filters. They argued that the effect of adversarial perturbation, which is widely spread in frequency domain, can be reduced when these filters are applied to audio adversarial examples. Their experimental results showed that audio adversarial examples have different result (\(\text{ASR}(x_{\text{adv}})\)) when they are modified using random filters (\(\text{ASR}(\text{RandFilter}(x_{\text{adv}}))\)), whereas benign audio waves have similar results (\(\text{ASR}(x)\)) even when they are modified in the same way (\(\text{ASR}(\text{RandFilter}(x))\)). Using this characteristic, the method distinguishes adversarial examples from benign audio waves by comparing the ASR results with and without filtering. The method, however, has difficulty of preventing over-air attacks because many over-air attacks consider the random filter scheme.

Temporal dependency. Zhuolin et al. [35] showed that audio sequences have explicit temporal dependency (e.g., correlations in consecutive waveform segments). To detect audio adversarial examples, they showed that adversarial effects are not effective when the adversarial audio is cut. Given an audio input, they selected its first \(k\) portion (the prefix of length \(k\)) as the input for ASR to obtain transcribed results as \(\text{ASR}(x)\}_{(k)}\), and inserted the whole input into the ASR and selected the prefix of length \(k\) of the transcribed result as \(\text{ASR}(x)\}_{\text{whole},(k)}\), which has the same length as \(\text{ASR}(x)\)\). Then, they compared the similarity between both results in terms of temporal dependency distance. The distance is small for benign audio waves and large for audio adversarial examples. However, the method does not consider over-air attacks. In addition, its average false positive rate is unsatisfactory based on a specific cutting ratio.

Audio reverberation. Xia et al. [12] proposed a robust detection method based on an audio reverberation technique. They pioneered the study of defense against robust over-air adversarial examples and discovered that audio adversarial examples are prone to overfitting and continuity. The overfitting is broken by room impulse response (RIR)-convolution method (\(H\)) into the input wave (\(\text{ASR}(x \ast H)\)). The RIR-convolution method can overcome the overfitting problem because it significantly modifies the audio waveform. To break the continuity, they found silent parts of the audio using voice activated detector (VAD) and inserted a Gaussian noise at these parts (\(\text{VAD}_{\text{silent}}(N)\)). Finally, they generated \(n\) results with \(n\) different RIR-convolutions and padded each silent part using random noise (\(\text{ASR}(x \ast H + \text{VAD}_{\text{silent}}(N))\)). They detected adversarial examples by calculating similarity scores of each of \(n\) transcription results with reverberation effect and that of the original audio wave. This method is somewhat effective at detecting over-air audio adversarial examples since various convoluted reverberations make the adversarial effect weaken. However, the method has a large time overhead because multiple inferences of generated waves are required.

4 PROPOSED METHOD

We propose logit noising, a novel detection method that can distinguish audio adversarial examples from benign audio waves. We aim to defend against both over-line attacks [8, 21, 32] and over-air attacks [9, 34] that have been launched on various settings (white-box or black-box). All the attacks considered are targeted ones aimed at producing a specific transcription. Benign audio waves have different logit value gap distributions from audio adversarial examples. Therefore, we focus on this logit value gap between them and design the proposed detection method to detect attacks by leveraging the difference in the logit value gap distributions.

The proposed system accepts input audio signals in the same way as the existing system and generates two results for similarity comparison. One is the transcription result with original logits of input wave signals, and the other is the agitated transcription result that is produced by adding a certain noise to each logit according to a given noise distribution before feeding the logits to the decoder of ASR. Then we compare the similarity of both results. Figure 4 is an overview of the proposed detection method.

4.1 Difference in Logit Value Gap Distribution

As explained in Section 2, an input audio wave is converted to a sequence of MFCC feature vectors and passed to the DNN acoustic model (AM). The DNN AM produces a sequence of outputs
corresponding to the input sequence. An output is called logits, each element of which represents the likelihood value of one character. Then the decoder (DE) uses the logits to produce a speech transcription.

We first carefully observe the distribution of the difference between the largest logit value and the remaining k-th logit values (1-k logit-gap) in the benign audio waves and audio adversarial examples. Figure 5a shows the 1-2 logit-gap, and Figure 5b shows the 1-3 logit-gap of 50 benign audio waves and 50 adversarial examples. The x- and y-axes represent the gap and the density of input samples corresponding to the gap, respectively. In the figure, the gap of adversarial examples is small and densely distributed with the center at 4 ~ 6, while the gap of benign audio waves is somewhat large and widely distributed for upto 10. The difference between benign samples and audio adversarial examples becomes more distinct as the value of k increases.

We conjecture that the audio adversarial examples have a densely distributed and smaller gap because they have to maintain a benign sound to human ears while producing the target phrase. On the other hand, the benign wave samples do not have such restrictions; therefore, the gap is widely distributed.

4.2 Logit Noising Architecture

To prevent the malicious transcription from being generated in the decoding step for audio adversarial examples, we use the logit noising strategy. As mentioned before, compared to benign audio waves, there is a smaller gap between the value of the largest logit and the values of the other logits of the audio adversarial examples. Hence, adding a certain noise to logits can thwart audio adversarial examples by corrupting only the adversarial examples. As we add noise to each logit, the order of logit values can be inverted. If inverted, the decoding step may produce a different transcription from the original transcription. If we choose a proper noise level with minimal effect on benign audio and significant effect on adversarial examples, the transcription of the benign waves will remain unchanged, whereas that of the adversarial examples will be changed.

Figures 6 and 7 show sample results of logit noising for a benign audio wave and an adversarial example. The audio adversarial example shows that many tokens are inverted compared with the benign audio wave, which is relatively robust to logit noising. To effectively detect audio adversarial examples, we developed a strategy to select appropriate noise and a detailed detection method.

Noise Selection. First, we calculate the probability that the largest logit value and the k-th largest logit value are inverted as a result of adding noise to each logit. Let L₁ and Lₖ be the values of the largest and the k-th largest logit, respectively. Then, the probability that the logit values are inverted owing to the added noise can be represented as follows:

\[
P_{\text{inv}}^{1,k}(w) = \sum_{m=1}^{n} (P_w(L_1 - L_k = c_m) 
\cdot P(c_m < (\epsilon(L_k) - \epsilon(L_1)) \mid L_1 - L_k = c_m))
\]

\[
= \sum_{m=1}^{n} P_w(L_1 - L_k = c_m) \int_{-\infty}^{\epsilon(L_k) - \epsilon(L_1)} P_e(x) \int_{x+c_m}^{\infty} P_e(y) dy dx
\]

where \(\epsilon()\), \(P_e()\), \(P_w()\), and \(n\) represent the noise, probability distribution of noise, probability distribution of logit values for the given input wave type \(w\), and the number of logits, respectively. Then we determine the total inversion probability as follows:

\[
P_{\text{total}}^{\text{inv}}(w) = (1 - \prod_{k=2} P_{\text{inv}}^{1,k}(w))
\]

Using the above equation, we can calculate the probability of inversion in various logit values as long as \(P_e()\) and \(P_w()\) are known. We obtain \(P_w\) by performing ASR inferences using sample waves (both adversarial and benign). For \(P_e()\), we determine a proper noise through the following analysis.

Determining a proper distribution for noise that inverts the logits of adversarial examples more than that of benign waves is challenging. We use Gaussian-distributed noise in this study, with the mean of the Gaussian distribution set at zero. As the largest logit is close to the second and third largest logit in the adversarial examples (Figure 5), subtle noise may induce inversions of adversarial examples without inverting the benign waves. Therefore, by varying the standard deviation (std) of the distribution, we are able to...
To determine whether a given input is an adversarial example or not, we measure the errors of the transcription result arising from the logit noising. We compute character error rate (CER) between the transcription results with and without logit noising. Let us denote $\text{ASR}(x) = \text{DE}(\text{AM}(x))$, then our detection method can be modeled as follows:

\[
\begin{align*}
\text{Find } P_e \text{ s.t. } P_{\text{total}}^{\text{adv}}(x) &\Rightarrow P_{\text{total}}^{\text{benign}}(x) \\
\end{align*}
\]

where $P_e$ represents the std of the noise distribution. The analysis of the experiments is explained in Subsection 5.2.

After determining the noise distribution, we apply the noise to logits and feed the results into the DE to produce a transcription result. We then compare the results with and without the logit noising. Let us denote $\text{ASR}(x) = \text{DE}(\text{AM}(x))$, then our detection method can be modeled as follows:

\[
\begin{align*}
\text{DE}(\text{AM}(x) + P_e) &\approx \text{DE}(\text{AM}(x)) & \text{if } x \neq x^{\text{adv}} \\
\text{DE}(\text{AM}(x^{\text{adv}}) + P_e) &\neq \text{DE}(\text{AM}(x^{\text{adv}})) & \text{otherwise}
\end{align*}
\]

4.3 Detecting Adversarial Examples

To determine whether a given input is an adversarial example or not, we measure the errors of the transcription result arising from the logit noising. We compute character error rate (CER) between the transcription results with and without logit noising. The CER is a metric that compares how different the character of generated sentence is from those of the original (ground-truth) sentence based on the Levenshtein distance [17]. The CER between two sentences is calculated using the following equation:

\[
\text{CER}(S_1, S_2) = \frac{I + S + D}{N}
\]

where $S_1$ and $S_2$ represent the original sentence characters and the generated sentence characters, respectively. In addition, $I$ is the number of insertion, $S$ is the number of substitution, $D$ is the number of deletion, and $N$ denotes the number of original sentence characters. We determine the optimal CER threshold via experiment.

Multiple instances of logit noising. As a noise sampled from a Gaussian distribution has randomness, the average result of multiple instances of logit noising can further increase the detection accuracy. First, we create multiple instances of logit noising by sampling multiple noises and adding them to logits. We then generate transcription results for each logit noising instance. We compute CERs between the transcription results of logit noising instances and the original logit. If the average CER falls below the threshold, the proposed system determines that the input wave is an adversarial example. In this paper, we empirically determine the number of logits noising instances to decide whether the given input is adversarial or not, and it is set to 4.

5 EXPERIMENTAL EVALUATION

5.1 Experimental Setup

We evaluate the effectiveness of the proposed method by applying it to DeepSpeech\textsuperscript{1} [15], which is Mozilla’s open source ASR system. We implement the proposed method using TensorFlow [1] and conduct all experiments on a workstation with one NVIDIA TITAN V GPU.

We use three over-line attacks [8, 21, 32] and two over-air attacks [9, 34] to evaluate the robustness of the proposed detection system. For the over-line attacks, we feed adversarial examples in a digital format (.wav file) directly to DeepSpeech (v0.1.0). We then compute the CER caused by logit noising. For the over-air attacks, we play the adversarial examples through the speaker and record the sound in a small room using a receiver that covers 0.5 m (Samsung Galaxy S8). Note that, we also play benign waves through the speaker and record as the same with adversarial examples for a fair comparison. Then, we compute CER and measure accuracy, false positive rate (FPR), and false negative rate (FNR) to evaluate the effectiveness of detection method. FPR is the rate at which a method mistakes benign audio waves for false adversarial

\textsuperscript{1}https://github.com/mozilla/DeepSpeech
Table 1: Target sentences used to generate adversarial examples

| Target sentences       | Long target sentences                                                                             | Short target sentences |
|------------------------|--------------------------------------------------------------------------------------------------|------------------------|
|                        | open the door                                                                                   | ok google              |
|                        | airplane mode on                                                                               | hello world            |
|                        | turn off the light                                                                             |                        |
|                        | this is adversarial example                                                                    |                        |
|                        | clear all appointments on calendar                                                             |                        |

We determine the parameters as follows. We set up \( s_t d \) of Gaussian noise and CER threshold that can effectively detect audio adversarial examples with long audio data, which is beneficial for long target sentences. On the other hand, the Taori attack is not suitable for long audio samples because of its high computing overhead [32]. For the Taori attack, we use 500 short data points to generate adversarial examples. The average lengths of the long and short data are 4.6s and 2.2s, respectively. We select target sentences based on the time length of the audio data. Target sentences for long and short data consist of three to five words and two words, respectively (See Table 1). The details of the datasets used in the experiments are summarized in Table 2.

5.2 Noise Parameter Selection

We set up \( s_t d \) of Gaussian noise and CER threshold that can effectively detect audio adversarial examples while having a low FPR. Low FPR is particularly important because an ASR system has to recognize benign audio as benign for maintaining its usability [3]. We determine the parameters as follows.

* We use publicly available adversarial examples.

**Table 2: Evaluation dataset composition**

| Attack Method | benign       | attack      |
|---------------|--------------|-------------|
| Over-line     | C&W          | 500 (long)  | 500         |
|               | weighted-sampling* | 6           | 11          |
| Taori         | 500 (short)  | 500         |
| Over-air      | Hiromu       | 500 (long)  | 500         |
|               | Metamorph*   | 4           | 16          |

First, we calculate the inversion probability \( P_{\text{inv}} \) of four types of waves, varying the \( s_t d \) values of Gaussian noise distribution (Figure 8). For this experiment, we use 50 benign waves, over-air benign waves, C&W (over-line) attack examples, and Hiromu attack examples (over-air). As can be observed from Figure 8, the \( P_{\text{inv}} \) difference between the audio adversarial examples and benign samples is noticeably different from when the \( s_t d \) is 3 (audio adversarial examples (0.4 and 0.45) and benign samples (0.02 and 0.24)), and the difference decreases from when the \( s_t d \) is 5 (audio adversarial examples (0.71 and 0.75) and benign samples (0.39 and 0.46)). We choose \( s_t d \) candidates (2-5) whose \( P_{\text{inv}} \) is low for benign waves and high for adversarial examples. Subsequently, we search for the optimal CER threshold for each \( s_t d \) candidates. For example, Figure 9a shows the results of over-line adversarial examples when \( s_t d \) is 3, and Figure 9b shows the results of over-air adversarial examples. We use a grid search to find the optimal CER and obtain the pairs of CER threshold and \( s_t d \). We show FPR and FNR against the over-line and over-air adversarial examples (Table 3). From the table, FPR is proportional to \( s_t d \), and FNR is inversely proportional to \( s_t d \). It is necessary to set an appropriate pair of \( s_t d \) and CER threshold, and we decide to use 3 for \( s_t d \) and 60 for CER threshold.

As we mentioned Section 4.3, we consider multiple instances of logit noising for a given input. We show the effect of multiple instance of logit noising in Table 4. We first calculate the CER of each instance and averaged them to decide whether the input is benign or adversarial example. The table shows FPR and FNR against the...
5.3 Detection Accuracy

Table 5 shows the performance of existing methods and the proposed method against various attacks. In the table, R.N.P. [16] represents the random noise padding method which detects attacks by modifying input waves using a low pass filter. TD1 and TD2 [35] represent the detection method that split input audio into 5:5 or 4:1 to find temporal dependencies between the split components. Reverb. [12] represents the detection method that adds reverberation noise to the input waves. Reverb. uses 4 different types of reverberation randomly for detection. For ours, we set $P_r$ to 3 and use four logit noising instances as above-mentioned. Each detection method uses different metrics to decide whether the input is benign or adversarial. Reverb. uses word error rate (WER), whereas TD1 and TD2 use character error rate (CER). We use CER instead of WER because the proposed method modifies logits, and that will directly affect each character unit.

From Table 5, it can be observed that most detection methods exhibit high detection accuracy for over-line attacks. For C&W and W-S attacks, the FNRs and FPRs of all detection methods are 0% (Acc.: 100%) except for TD1 and TD2. Although the TD1 and TD2 methods cannot detect all the over-line attacks, TD1 and TD2 methods show high accuracy (TD1: 92.3 % & TD2: 95.8 %). Against the Taori attack, only the Reverb. and the proposed method achieve 0% FPR and 0% FNR. Although other methods suffer from high false positives and false negatives, these methods achieve comparable accuracy. These results imply that all the detection methods effectively detect adversarial examples of over-line attacks.

The most noticeable point is the result of over-air attacks. R.N.P., TD1, and TD2 have high FNR (from 98.6% to 58.8% against the Hiromu attack and from 100% to 56.25% against the Metamorph attack). The results indicate that these detection methods have limited performance at detecting over-air adversarial examples, although they recognize benign samples well.

In contrast to existing methods, the proposed method exhibits low FNR and FPR for all over-air attacks. Furthermore, it shows a low FPR (0.6% against the Hiromu attack and 6.25% against the Metamorph attack). These results demonstrate that our detection method is more robust than the other methods for over-air adversarial examples.

6 DISCUSSION

Our experiments show that the proposed method, which adds noise to the logit, can detect audio adversarial examples effectively without additional components.

Logit Distribution Difference. The preceding analysis of our experiment shows that the logit-gap distribution of benign audio waves is different from that of audio adversarial examples. The logit-gap of audio adversarial examples is densely distributed than that of benign waves. We conjecture that the largest logit is for the target phrase and other logits are for the original wave when an adversarial example is successful. As the adversarial example has to resemble human-audible original wave, the logit-gap of the audio adversarial examples is small. This phenomenon makes the proposed method detect audio adversarial examples effectively.
Table 5: Evaluation of various detection methods for different attacks.

| Type       | Attack (Dataset) | Performance | Detection method |
|------------|------------------|-------------|------------------|
|            |                  | Accuracy    | Reverb. (n=4) [12] | ours (std=3) |
| Over-line  | C&W (Dlong) [8]  | Accuracy    | 1000 (100%)       | 1000 (100%) |
|            |                  | FPR         | 0 (0%)            | 0 (0%)       |
|            |                  | FNR         | 0 (0%)            | 0 (0%)       |
| Over-air   | W-S (-) [21]     | Accuracy    | 1000 (100%)       | 1000 (100%) |
|            | Hiromu* (Dlong) [34] | Accuracy | 998 (99.8%)       | 1000 (100%) |
|            |                  | FPR         | 0 (0%)            | 0 (0%)       |
|            |                  | FNR         | 0 (0%)            | 0 (0%)       |
|            | Metamorph* (-) [9] | Accuracy | 507 (50.7%)       | 990 (99.0%)  |
|            |                  | FPR         | 0 (0%)            | 0 (0%)       |
|            |                  | FNR         | 2 (0.4%)          | 0 (0%)       |

* means dataset recorded over-air.

Noisy Distribution. In this paper, we only use Gaussian noise distribution. We think that there are some noise distributions that may not work depending on the distribution of the gap value. We consider that it may need a tailored noise distribution that will separate benign samples and adversarial examples.

Type of Source Wave. We have shown results experimented with a human voice in LibriSpeech dataset. As attacks with various input wave types have been proposed [18, 36], we have also conducted experiments on song wave type. In this experiment, we only focus on false negative rate (FNR). This is because the song may not contain any transcription, and the target model (DeepSpeech v0.1.0) does not recognize song with a lyric well. The logit noise method is able to detect song based audio adversarial examples well (FNR: 98.11%).

ASR Platform. We have conveyed our study on DeepSpeech platform. We have not considered attacks built on other platforms like Kaldi [26] & Lingvo [31]. However, other platforms also adopt MFCC as acoustic model’s input, and the proposed method only uses acoustic model result (logits). Therefore, we believe that our method also works on them.

Future work. One thing we carefully consider is whether our method can be used to recover original sentences from adversarial examples. We have experimented with different distribution of Gaussian noise. There are some cases that have recovered original transcription results when the perturbed signal in adversarial example is subtle. However, when there is a huge perturbation to make adversarial examples, the sound is a little noisy and it is unable to recover original transcription from logit noise. We think it needs further study to recover the original transcription using logit noise.

Adaptive attacks can be considered for future work. Although our method has a great effect on various types of attack, we do not consider adaptive attackers who know the logit noise detection method. However, we predict that it is difficult to make robust logit noise for adversarial examples, not like benign samples, through adaptive attacks because considering both generating target transcription from continuous vector frames and making the largest logit value and another logit values require high computational cost.

7 CONCLUSION

In this paper, we introduce a novel and simple audio adversarial example detection method applicable to speech recognition systems. We discover that audio adversarial examples are distinguishable by adding noise to logits before feeding them into the ASR decoder. To evaluate our proposed system, we experiment with an open-source speech recognition system, DeepSpeech. We evaluate various attacks, including three over-line attacks and two over-air attacks. We demonstrate that the accuracy of our method is higher than that of existing state-of-the-art methods. Most importantly, our method is effective at detecting over-air attacks. The proposed method is easy to implement and does not require model retraining. We expect our results to provide another avenue to detect audio adversarial attacks.

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