SPOOFED TRAINING DATA FOR SPEECH SPOOFING COUNTERMEASURE CAN BE EFFICIENTLY CREATED USING NEURAL VOCODERS

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ABSTRACT
A good training set for speech spoofing countermeasures requires diverse TTS and VC spoofing attacks, but generating TTS and VC spoofed trials for a target speaker may be technically demanding. Instead of using full-fledged TTS and VC systems, this study uses neural-network-based vocoders to do copy-synthesis on bona fide utterances. The output data can be used as spoofed data. To make better use of pairs of bona fide and spoofed data, this study introduces a contrastive feature loss that can be plugged into the standard training criterion. On the basis of the bona fide trials from the ASVspoof 2019 logical access training set, this study empirically compared a few training sets created in the proposed manner using a few neural non-autoregressive vocoders. Results on multiple test sets suggest good practices such as fine-tuning neural vocoders using bona fide data from the target domain. The results also demonstrated the effectiveness of the contrastive feature loss. Combining the best practices, the trained CM achieved overall competitive performance. Its EERs on the ASVspoof 2021 hidden subsets also outperformed the top-1 challenge submission.

Index Terms— anti-spoofing, presentation attack detection, countermeasure, logical access, neural vocoder

1. INTRODUCTION
The detection of speech produced by text-to-speech (TTS) and voice conversion (VC) systems is a well-established but unresolved research topic [1, 2]. Most studies use machine-learning-based approaches, and they train a classification model (a.k.a spoofing countermeasure (CM)) on a training set that contains both human (bona fide) and synthesized (spoofed) speech data. The trained CM is then used to detect unseen test data.

Creating high-quality and diverse spoofing data requires tremendous effort. For example, the ASVspoof 2019 challenge logical access (LA) database [3] was constructed with the help of more than ten organizations over six months. Furthermore, spoofing methods are constantly evolving. For real applications, practitioners may need to update the CM training data from time to time. Although some TTS and VC algorithms with zero-shot learning [4, 5] make it easier to generate speech for any speaker, they cover only part of the existing TTS-VC paradigms. Collecting spoofed data from diverse TTS and VC systems is still demanding.

This study investigates an alternative way to create spoofed data for CM training. Instead of using full-fledged TTS and VC systems, this study uses the vocoder, a last-step module in both TTS and VC systems, to create spoofed data in a copy-synthesized manner. Specifically, acoustic features such as Mel-spectrogram are extracted from a bona fide waveform and fed to a vocoder to re-synthesize the waveform. The copy-synthesized or vocoded waveform is treated as spoofed data. While vocoded data is different from TTS/VC-synthesized data because the latter is generated given predicted acoustic features, both carry artifacts inherent to the vocoder. Thus, it is presumably possible to train a CM using vocoded spoofed data and use it to detect spoofed data from actual TTS/VC systems. Furthermore, vocoded data is easier to obtain than TTS/VC-synthesized data since most vocoders do not require text transcription, grapheme-to-phoneme conversion, or speaker embeddings. Training a universal vocoder is also comparatively easier than training a TTS/VC system.

Vocoded spoofed data has been used for CM training in the past. In [6, 7, 8], vocoded data produced by digital-signal-processing (DSP)-based vocoders was used to teach a CM to spot phase distortion caused by these vocoders. A more recent database called WaveFake gathers vocoded spoofed data from advanced deep-neural-network (DNN)-based vocoders [9], but the data is only from two speakers. Neither is it reported how a CM trained on WaveFake generalizes to other test sets.

In this study, we plan to answer three questions: 1) Is there any caveat when using the latest neural vocoders to create useful vocoded spoofed data? 2) Is there any method that can make good use of bona fide and vocoded data pairs and better train the CM? 3) How well does the CM generalize to actual and advanced TTS and VC spoofing attacks? On the basis of the bona fide data in the ASVspoof 2019 training set [3], we build a few training sets with vocoded spoofed data to address the first question. We then introduce a contrastive feature loss to address the second question. Answers to all the questions are examined through experiments that used the prepared training sets and multiple benchmark test sets with diverse TTS and VC attacks. The results suggest a few practices for training set creation. They also demonstrate that a CM trained using the best training set in this study and the contrastive feature loss performed well on detecting challenging spoofing attacks and in a few cases better than other CMs in the literature.

2. METHODS

2.1. Creating Spoofed Data Using Vocoders
Creating vocoded data is straightforward: collecting natural (bona fide) speech data, extracting acoustic features, and driving the vocoder to synthesize waveforms. Many open-sourced and pre-trained vocoders can be used off-the-self, fine-tuned or re-trained from scratch. However, there are factors we should be aware of. For example, which vocoder should be included? Is there any mismatch between the sampling rate of the bona fide data and that required by the vocoder? Is there any domain mismatch between the vocoder’s training data and the bona fide data for copy-synthesis?
The first factor is also a practical one because the generation speed of some DNN-based vocoders (e.g., autoregressive (AR) models like WaveNet [10]) is more than 100 times slower than real-time [11]. Most users, including us, cannot afford the time to generate even a small amount of vocoded data. Therefore, we investigate only non-AR neural vocoders:

- General-adversarial-network-based: HiFiGAN [12], Parallel WaveGAN (PWG) [11], MultiBand MelGAN [13];
- Fusion of DNN and DSP: Harmonic-plus-noise neural source-filter model (Hn-NSF) [14]; combination of Hn-NSF and HiFiGAN (NSF-HiFiGAN) [15];
- Flow-based: WaveGlow [16].

Another reason to choose the above vocoders is that they have reliable implementations released.

As for other factors such as sampling rate and data domain mismatch, we created a few training sets with vocoded spoofed data and empirically investigated what caveat should be cautioned against. Specifically, we used the bona fide data from the ASVspoof 2019 LA training set (LA19trn) and prepared different versions of vocoded spoofed data using the vocoders above. The created training sets are listed in Table 1 and described below:

- **Voc.v1** follows the WaveFake training subset (WFtrn)2 and used four vocoders pre-trained by ESPNet [17] on a multi-speaker database called LibriTTS [18]. However, since these vocoders operate at a sampling rate of 24 kHz, the 16-KHz bona fide data to be vocoded was up-sampled to 24 kHz, and the vocoded data was down-sampled back to 16 kHz.
- **Voc.v2** requires no change of sampling rate during copy-synthesis. The spoofed data was created using our own implemented vocoders trained on LibriTTS and operating at 16 kHz. The vocoders cover the three categories listed above.
- **Voc.v3** is similar to Voc.v2, but vocoders were trained from scratch on the bona fide data of LA19trn.
- **Voc.v4** is similar to Voc.v2, but vocoders from Voc.v2 were further trained on the bona fide data of LA19trn.

Note that all the above training sets have the same amount of bona fide data as LA19trn. Comparisons among Voc.v2, Voc.v3, and Voc.v4 are expected to show the impact of data domain mismatch, while comparison between Voc.v2 and Voc.v1 can be helpful for understanding the impact of the sampling rate.

### 2.2. Contrastive Feature Loss for Bona Fide and Vcoded Data

Vocoded spoofed data has (almost) the same duration and tempo as the corresponding bona fide utterance, which has at least two merits. First, potential data artifacts caused by an imbalanced distribution of duration in bona fide and spoofed data (e.g., length of non-speech regions [2, 19]) can be avoided. Second, acoustic feature sequences extracted from spoofed and bona fide utterances are aligned with each other, and useful contrastive information can be derived.

To make good use of the contrastive information, we introduce an auxiliary contrastive feature loss for CM training. Suppose that we have a bona fide utterance \(o_{1:T,1}\) of length \(T\) and \(K\) augmented utterances \(\{o_{1:T,2}, \ldots, o_{1:T,K+1}\}\). Let us use \(S\) vocoders to create spoofed vocoded data for the \(1 + K\) bona fide utterances, after which we get \(S(1 + K)\) vocoded utterances. With a CM feature extractor, let \(\mathbf{x}_{1:N,i}\) and \(\mathbf{x}_{1:N,j}\) be the feature sequence extracted from \(o_{1:T,i}\) and \(\mathbf{̂x}_{1:T,j}\), where \(i \in \mathcal{I} = \{1, 2, \ldots, (1 + K)\}\) and \(j \in \mathcal{J} = \{1, 2, \ldots, S(1 + K)\}\), respectively. If we create a mini-batch using \(\mathbf{x}_{1:N,i}, \forall i \in \mathcal{I}\) and \(\mathbf{̂x}_{1:N,j}, \forall j \in \mathcal{J}\), the contrastive feature loss over the mini-batch can be defined as

\[
\mathcal{L}_{CF} = - \sum_{i \in \mathcal{I}} \frac{1}{|\mathcal{I}| - 1} \frac{1}{p \in \mathcal{I}, p \neq i} \log \frac{\exp(f(\mathbf{x}_{1:n,i}, \mathbf{x}_{1:n,p}))}{\mathcal{H}(\mathbf{x}_{1:n,i})} - \sum_{j \in \mathcal{J}} \frac{1}{|\mathcal{J}| - 1} \frac{1}{q \in \mathcal{J}, q \neq j} \log \frac{\exp(f(\mathbf{̂x}_{1:n,j}, \mathbf{x}_{1:n,q}))}{\mathcal{H}(\mathbf{̂x}_{1:n,j})},
\]

where \(\mathcal{H}(\mathbf{x}) = \sum_{1 \leq i \leq |\mathcal{I}|} \exp(f(\mathbf{z}, \mathbf{x}_{1:n,i}) + \sum_{1 \leq j \leq |\mathcal{J}|} \exp(f(\mathbf{z}, \mathbf{̂x}_{1:n,j})) - \exp(f(\mathbf{z}, \mathbf{z})), |\mathcal{I}| = K+1, |\mathcal{J}| = S(1+K)\), and where we drop the time sequence subscript \(1:N\) in \(\mathbf{x}_{1:n,i}\) and \(\mathbf{̂x}_{1:n,j}\). The \(f(\mathbf{x}_{1:n,i}, \mathbf{x}_{1:n,p}) = \frac{1}{N} \sum_{n=1}^{N} \sum_{p=1}^{P} (\mathbf{x}_{1:n,i,p} - \mathbf{x}_{1:n,p})^2\) measures the cosine similarity averaged over the feature vector pairs \(\{\mathbf{x}_{1:n,i}, \mathbf{x}_{1:n,p}\}, \forall n \in \{1, \ldots, N\}\). The hyper-parameter \(\tau\) is fixed to 0.07 following [20].

\(\mathcal{L}_{CF}\) in Eq. (1) is a special case of supervised contrastive loss [20] that considers only two classes (i.e., bona fide and spoofed). A difference is that the similarity \(f()\) is computed between two aligned feature sequences, while it can be used for utterance-level features with \(N = 1\). In this study, \(\mathcal{L}_{CF}\) is directly merged with the conventional cross-entropy loss for CM training, i.e., \(\mathcal{L}_{CE} + \mathcal{L}_{CF}\). It is expected to drive the features of the data in the same class to be closer to each other while pushing away those from a different class.

### 3. Experiments

The first part of the experiments compares the training sets created in Section 3.1 with a standard training set. The goal is to identify factors that one should be alerted to when creating vocoded spoofed data. The second part examines the performance of the contrastive feature loss introduced in Section 2.2. With the experimental results, we give tentative results to the questions raised in Introduction.

#### 3.1. Datasets

The CM training sets used in the experiments included those listed in Table 1 and the commonly used ASVspoof 2019 LA training set (LA19trn) for reference. The development set was the ASVspoof 2019 LA development set no matter which training set was used.

Eight test sets were used to fairly measure the CM performance. They included the test sets from ASVspoof 2019 LA (LA19eval), the evaluation subsets of ASVspoof 2021 LA (LA21eval), and the 2021 DF (DF21eval) tasks. Since CMs may overfit to the length of non-speech segments [2, 19], we included another version of the three test sets in which the non-speech segments were trimmed. Two of them (LA21hid and DF21hid) are the official hidden subsets in the ASVspoof 2021 LA and DF datasets [2], and the other one, LA19etrim, was created by us given LA19eval1. The last two test sets were the entire WaveFake (WaveFake) and In the Wild datasets (InWild21). Note that, since the training set WFtrn is a subset of WaveFake, we excluded the result if a CM
Table 1: CM training sets with vocoded spoofed data. For reference, ASVspoof 2019 LA training set (LA19trn) contains 2,580 bona fide and 22,800 spoofed trials from 20 speakers at sampling rate of 16 kHz. Right-most column is sampling rate (SR) that vocoder works on.

| ID | #. Spr. | #. Bona. | #. Spoof. | Vocoder type | Implementation | Vocoder train/fine-tune data | Vocoder SR |
|----|---------|----------|-----------|--------------|----------------|-----------------------------|------------|
| WFtrn | 1 | 3,930 | 15,720 | HiFiGAN, MB-MelGAN, PWG, WaveGlow | ESPNet toolkit | LibriTTS / - | 24 kHz |
| Voc.v1 | 20 | same as WFtrn | 2,580 | 10,320 | HiFiGAN, MB-MelGAN, PWG, StyleMelGAN | ESPNet toolkit | LibriTTS / - | 24 kHz |
| Voc.v3 | LA19trn | 2,580 | 10,320 | HiFiGAN, NSF-HiFiGAN, Hn-NSF, WaveGlow | in-house | LibriTTS / - | 16 kHz |
| Voc.v4 | | | | HiFiGAN, NSF-HiFiGAN, Hn-NSF, WaveGlow | in-house | LibriTTS / LA19trn bona. | 16 kHz |
| Voc.v4 | | | | HiFiGAN, NSF-HiFiGAN, Hn-NSF, WaveGlow | in-house | LibriTTS / LA19trn bona. | 16 kHz |

was trained on WFtrn and tested on WaveFake. We used the entire WaveFake as a test set so that the results can be compared with other literature. Note that WaveFake contains three more vocoders not covered by any training data in Table 1. The InWild is a recently released dataset containing bona fide and spoofed trials from more than 50 English-speaking celebrities and politicians. The data has more diverse acoustic characteristics and is more challenging [21].

3.2. Training Recipe and Evaluation Metric

The same CM architecture was used in all the experiments: a two-staged model with a self-supervised learning (SSL)-based feature extractor and a feedforward classifier. The SSL feature extractor was a pre-trained Wav2vec 2.0 model [22]. The classifier consisted of a global average pooling layer, a neural network with three fully-connected layers and LeakyReLU activation functions, and a linear output layer for binary classification. The weights of the pre-trained SSL feature extractor were updated during CM training. Similar SSL-based CMs have shown better generalization performance [23, 24]. Additional experiments were also conducted on two other CMs without a SSL feature extractor, but the results were not satisfying. Those additional results are uploaded to Arxiv.

The CMs used the Adam optimizer ($\beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 10^{-8}$) [25]. The learning rate was initialized to $5 \times 10^{-6}$ and multiplied by 0.1 every ten epochs. The training process was stopped when the loss on the development set did not improve within ten epochs. The batch size was eight, but when the contrastive feature loss was used, each mini-batch contained one bona fide utterance and its four vocoded versions. The training data were truncated into segments with a maximum duration of 4s to fit the GPU memory. During inference, the whole trial was processed without truncation.

CM performance was measured using the equal error rate (EER). The EER was calculated on each individual test set and the pooled test set. Each CM was trained and evaluated for three rounds, where each round used a different random seed to initialize the network weights. The EER averaged over the three rounds is reported.

3.3. Experiment 1: Comparing Vocoded Training Sets

This experiment investigated the effectiveness of the training sets with vocoded spoofed data listed in Table 1. The LA19trn and WFtrn were also included for reference. The CM was trained on each training set with the standard binary CE loss $L_{CE}$. From the results listed in Table 2, we first note that the EERs given LA19trn were similar to those reported in [23]. This indicates that the CM and training recipe worked as expected.

Compared with the standard training set LA19trn, the EERs when using vocoded training sets were higher on the first three test sets. However, this may be because the CM trained on LA19trn exploited non-speech segments that unevenly distributed in bona fide and spoofed trials [2, 19]. On other test sets, the CM trained on Voc.v4 achieved lower EERs. The results obtained on the vocoded training sets allowed us to answer whether there is any caveat when creating useful vocoded spoofed data. Described below are our tentative suggestions:

Avoid waveform re-sampling during copy-synthesis: Although the vocoders in Voc.v1 and Voc.v2 are not the same, the larger EERs in Voc.v1 may be partially caused by re-sampling. This hypothesis was supported by another experiment using the HiFiGAN models operating at 24 and 16 kHz (see Appendix). Neural vocoders, which have never been trained on re-sampled waveforms, may produce artifacts in vocoded data if the input bona fide data is re-sampled. CMs that overfit to those artifacts may not generalize to realistic spoofing attacks that do not do re-sampling.

Tune neural vocoders to target domain: From comparisons among Voc.v2, Voc.v3, and Voc.v4, we observe that it is preferable to let neural vocoders learn from the bona fide data from which the vocoded spoofed data are to be created. This can be done by training the neural vocoders from scratch or fine-tuning pre-trained neural vocoders using the bona fide data. The WFtrn training set did not perform well probably because of the domain mismatch and limited number of speakers.

3.4. Experiment 2: Effect of Contrastive Feature Loss

With the promising result of Voc.v4 in Experiment 1, we investigated whether the CM performance can be further improved if the vocoded spoofed data can be put to good use. The method examined was the contrastive feature loss ($L_{CF}$ in Eq. (1)), which was computed on both the SSL-based front-end’s output sequence and the utterance-level vector after global average pooling. We trained a few CMs with different configurations listed in Table 3. Marked by $\oplus$ is the experimental CM trained using $L_{CF} + L_{CE}$. Each
Table 3: Test set EERs (%) of Experiment 2. Each column corresponds to CM trained using specific configuration. Darker cell color indicates higher EER value. Results in columns ① and ② are copied from Table 2 as reference.

| Training criterion | \( L_{CE} \) | \( L_{CE} + L_{CF} \) |
|--------------------|------------|-----------------|
| Data augmentation  | × RawBoost | RawBoost |
| Training set       | LA19 Voc. v4 | LA19 Voc. v4 | LA19 Voc. v4 |
| Bona-spoof paired ID | ① ② ③ ④ ⑤ ⑥ ⑦ |
| LA19eval           | 2.98 4.36 0.22 3.46 0.21 2.63 2.21 |
| LA21eval           | 7.53 24.39 3.63 16.55 3.30 16.67 17.90 |
| DF21eval           | 6.67 13.31 3.65 9.60 4.12 6.92 5.04 |
| LA19etrim          | 15.56 9.52 9.16 6.09 9.00 4.48 3.79 |
| LA21hid            | 28.80 21.43 21.18 19.37 26.98 15.05 14.57 |
| DF21hid            | 23.62 16.99 13.64 14.29 16.85 8.17 7.78 |
| WaveFake           | 15.76 10.89 26.37 6.87 24.62 4.03 2.50 |
| InWild             | 26.65 19.45 16.17 12.08 17.07 9.37 7.55 |
| Pooled             | 14.24 16.35 13.12 13.13 13.68 13.15 11.27 |

mini-batch for ⑦ contained a bona fide trial, its vocoded spoofed data from the four neural vocoders, and one piece of augmented data for each trial (i.e., \( S = 4 \) and \( K = 1 \) for \( L_{CE} \)). The data augmentation was done using RawBoost [27].

For comparison, CM ⑥ used the same setting as ⑦ except that the spoofed trial in each mini-batch was randomly selected and was not paired with the bona fide trial. ⑤ was the same as ⑥, but the training data was from LA19trn. Note that the mini-batch cannot include paired bona fide and vocoded spoofed trials when using LA19trn. ④ and ③ further removed \( L_{CF} \). Finally, ② and ① are from Experiment 1 and were included as reference.

Results suggest that the contrastive feature loss can improve the CM when it is used together with a training set that contains vocoded spoofed data. From ② to ④ and then ⑦, we observe that the overall pooled EER decreased from 16.35% to 11.27%. While the comparison between ② and ④ suggests that data augmentation such as RawBoost is helpful, the comparison between ④ and ⑦ implies that adding the contrastive feature loss brings in additional improvement. Furthermore, a comparison between ⑥ and ⑦ suggests that using a bona fide trial and its corresponding vocoded spoofed data in each mini-batch is also helpful.

The gain brought by the contrastive feature loss diminishes when using LA19trn. This can be observed from the comparison between ③ and ⑤. Hence, it is recommended to add the contrastive feature loss when using a training set with vocoded spoofed data.

3.5. Analysis and Comparison with Other Literature

Since CMs trained on Voc.v4 were exposed only to a limited number of neural vocoders, do they generalize to TTS and VC spoofing attacks using unseen vocoders? To answer this question, we followed [2] and analyzed the score distributions after grouping the trials in DF21hid according to the category of the vocoder used in the spoofing TTS and VC systems. The three categories were neural AR, neural non-AR, and traditional DSP-based vocoders. Scores given by CM ⑦ are plotted in Fig. 1. As expected, the CM performed worse on spoofed trials with neural AR vocoders since the CM training data does not cover similar vocoders. While DSP-based vocoders are also unseen, the CM trained on Voc.v4 seemed to be generalizable. Similar results were observed on other test sets that had labels of spoofing attacks (see results on Arxiv). In short, a CM trained on bona fide and vocoded spoofed data may not perfectly generalize to spoofing attacks from unseen vocoder types.

Despite the limitation, we highlight that the best CM ⑦ in this study has demonstrated competitive performance in detecting actual TTS/VC attacks. From the comparison with results in other literature listed in Table 4, it is clear that the EER of ⑦ outperformed the others on all the test sets except LA19eval and LA21eval. The unsatisfactory performance on LA21eval may be alleviated if we use a codec for data augmentation. This is left for future work.

4. CONCLUSION

This study investigated an alternative way to create a training set for spoofing CM. Instead of building full-fledged TTS and VC systems, this study simply created spoofed data by conducting copy-synthesis on bona fide utterances using neural vocoders. Multiple training sets were created on the basis of the ASVspoof 2019 LA training set and compared in the experiments. Furthermore, this study introduced a contrastive feature loss to better use the bona fide trials and their corresponding vocoded spoofed data.
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