Adversarial Speaker Distillation for Countermeasure Model on Automatic Speaker Verification

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Abstract
The countermeasure (CM) model is developed to protect ASV systems from spoof attacks and prevent resulting personal information leakage in Automatic Speaker Verification (ASV) system. Based on practicality and security considerations, the CM model is usually deployed on edge devices, which have more limited computing resources and storage space than cloud-based systems, constraining the model size under a limited budget. To better trade off the CM model sizes and performance, we proposed an adversarial speaker distillation method, which is an improved version of knowledge distillation method combined with generalized end-to-end (GE2E) pre-training and adversarial fine-tuning. In the evaluation phase of the ASVspoof 2021 Logical Access task, our proposed adversarial speaker distillation ResNetSE (ASD-ResNetSE) model reaches 0.2695 min t-DCF and 3.54% EER. ASD-ResNetSE only used 22.5% of parameters and 19.4% of multiply and accumulate operands of ResNetSE model.

Index Terms: Automatic Speaker Verification, Anti-spoofing, GE2E Pre-training, Adversarial Fine-tuning, Knowledge Distillation

1. Introduction
Automatic speaker verification (ASV) is a method for determining if a certain utterance is spoken by an individual. This is one of the most important technologies for biometric identification, which is widely used in real-world applications, including smartphones, smart speakers, digital wallets, etc. Through active research on various methods [1–4], significant performance improvements have been created in accuracy and efficiency of ASV systems. The earliest proposed method [1] used the Gaussian mixture model to extract acoustic features and then computes a score based on the likelihood ratio. Recently, end-to-end ASV models such as [4, 5] have been proposed to directly map utterances to verification scores. End-to-end models improve verification accuracy, making the ASV model compact and efficient.

The ASVspoof challenge series [6–9] were held to encourage researchers developing strong countermeasure (CM) models against spoofing audio signals such as synthetic, converted, and replayed. ASVspoof 2021 consists of three subtasks: logical access (LA), deepfake (DF), and physical access (PA). This paper focuses on the LA subtask, where the spoofing audio signals are generated from either text-to-speech (TTS) or voice conversion (VC) systems. Despite the power of today’s TTS and VC technology, subtle differences still exist between spoofs and raw audio streams. A variety of CM models for LA [10–20] using GRCCNs, VGG, SE-Net, or LCNN have been proposed to detect spoofing audio signals. Both ASV and anti-spoofing model have also been proven vulnerable to adversarial attack [21, 22]. A variety of defense methods have been proposed to well improve the robustness of ASV and anti-spoofing model against adversarial attacks [23–28]. The biggest commonality between the generated spoofing audio and the adversarial attack audio is that they influence the decisions of the countermeasure model in imperceptible ways.

Some ASV systems [29,30] are running on edge devices, in order to avoid network transmission failure. The CM model is often used in conjunction with the ASV model. In edge devices, the models need to be lighter to account for limited computing power and storage space. Knowledge distillation (KD) [31] is one classical method used to reduce the model size, where the knowledge is transferred from a larger teacher model to a more lightweight student model. However, KD often degrades the performance while reducing the model size of the model. To maintain or prevent the model performance degradation after distillation, one straightforward motivation is to train a powerful teacher model firstly.

To enable the CM system to sense the gap between the audio produced by TTS and VC technology and the real audio, we separate the embeddings of different spoofing condition and narrow those of the same spoofing condition. We also utilize the adversarial example to further improve the ability of CM model to perceive the subtle difference between modified and bona fide audio, which inspired by training by adversarial example can easier perceive the subtle perturbation in ASV task [27]. In this paper, we mainly have the following contributions:

1) To our best knowledge, this is the first to explore the lightweight ASV spoofing CM model.

2) We proposed an adversarial speaker distillation method, which combined with generalized end-to-end (GE2E) [32] pre-training and adversarial fine-tuning for the teacher model, and use KD to obtain the student model.

3) Experiments showed that our proposed training strategies effectively improved student model performance, while maintaining a good balance between performance and resource consumption.

2. Methods
In this paper, we designed an adversarial speaker distillation training strategy and used ResNetSE [33] as backbone model. The establishment of the teacher model involved two steps: pre-training, and fine-tuning. The teacher model, which is named as GE2E-ResNetSE, is pre-trained by GE2E loss and adversarial fine-tuned by negative log-likelihood (NLL) loss. Note that adversarial fine-tuning means injecting an adversarial speaker class into the original dataset. The student ResNetSE (ASD-ResNetSE) distilled adversarial speaker knowledge from GE2E-ResNetSE. Each utterance has two labels, namely the

* Equal contributions.
This step, the GE2E loss was computed using the pooling layer of ResNetSE (Figure 2 (a)). In the second step, we fine-tuned the whole model with the ASVspoof2021-provided data and the injected adversarial data generated by AEG. This process makes the model focus on distinguishing fake audio streams from bona fide ones.

### 2.2.1. Generalized End-to-End Pre-training

GE2E loss [32] was proposed for speaker verification, and a variant of this approach has been used to detect replayed spoofing attacks (PA subtask of ASVspoof 2021) [35]. In this paper, we use GE2E loss calculated according to spoofing condition classes in LA subset to obtain the initial model. Firstly, each batch included $M$ utterances from one of the $N$ different conditions. The utterances $x_{nm}$ in the batch (except the query itself) formed the centroids $c_n$ of each condition, where $1 \leq n \leq N$, $1 \leq m \leq M$. The formula of $c_n$ is defined as:

$$c_n = \frac{1}{M} \sum_{m=1}^{M} x_{nm} \quad (1)$$

Each utterance embedding was expected to be close to its corresponding spoofing condition centroid, but far from the centroids of other spoofing conditions. Thus, a similarity matrix $S_{nm,k}$ was defined to describe the scaled cosine similarity of utterances with centroids $k$, where $w, b$ are learnable parameters in the expression:

$$S_{nm,k} = w \cdot \cos(x_{nm}, c_k) + b \quad (2)$$

Softmax was applied to the similarity matrix for every category (from 1 to $N$) when calculating GE2E loss. The overall loss function was defined in equation 3, which means that utterance embeddings of the same spoofing condition should be close to each other, and far from those of other spoofing conditions.

$$L_{GE2E} = -S_{nm,n} \log \sum_{k=1}^{N} \exp(S_{nm,k}) \quad (3)$$

### 2.2.2. Adversarial fine-tuning

After the teacher model was initialed by GE2E pre-training, it will be fine-tuned using NLL loss with spoofing condition label. The spoofing condition label is composed of 8 classes: 1 bona fide, 6 spoof methods, and 1 adversarial speaker. The additional adversarial speaker class is generated by the Adversarial Example Generation (AEG) algorithm described below.

AEG was a process that deliberately generated a tiny perturbation to the original example to generate a adversarial audio. This work adopted the basic iterative method (BIM) [36] for AEG. The audio input of the AEG algorithm was a same-speaker randomly-selected bona fide audio signals $W_1$ and $W_2$, and the output was the newly generated example. $\text{Extract Feature}(M, W)$ meant using model $M$ to extract features for $W$. The score $s$, indicating the similarity between the forged and the original audio. Only the new example with $s$ smaller than threshold will be used as an adversarial sample. The algorithm is shown in detail in Algorithm 1. Based on this, we implemented two AEG methods, static AEG and active AEG.

**Static AEG.** Static AEG used the GE2E pre-trained model as the input for Algorithm 1 to generate attack data. All the generated attack data will be relabeled as an adversarial example and injected into the original data set. Since all data were created...
before fine-tuning, static AEG did not increase the overhead of fine-tuning.

**Active AEG.** The difference between static AEG and active AEG was that active AEG executed BIM before each epoch, which means that the same input audios will produce different adversarial samples in different epochs. Although this additional work may increase training time, active AEG is expected to generate more architecture-specific data.

**Algorithm 1 Basic Iterative Method (BIM)**

**Require:** Two audios, \( W_1 \) and \( W_2 \) belonging to the same speaker. Model \( M \). \( \alpha \), iter, and threshold are controllable variables.

**Ensure:** Feature of the forged audio.

\[
\begin{align*}
1: & \quad X_1 \leftarrow \text{Extract\_feature}(M, W_1) \\
2: & \quad D \leftarrow \text{Zero\_array}(\text{len}(W_1)) \\
3: & \quad \text{for } t \leftarrow 1 \text{ to iter do} \\
4: & \quad \quad X_2 \leftarrow \text{Extract\_feature}(M, W_2 + D) \\
5: & \quad \quad s \leftarrow \text{Cos\_similarity}(X_1, X_2) \\
6: & \quad \quad D \leftarrow \text{clip}(D + \alpha \times \text{sign}(D(s))) \\
7: & \quad \text{end for} \\
8: & \quad X_2 \leftarrow \text{Extract\_feature}(M, W_2 + D) \\
9: & \quad s \leftarrow \text{Cos\_similarity}(X_1, X_2) \\
10: & \quad \text{if } s \leq \text{threshold} \text{ then} \\
11: & \quad \quad \text{return NULL} \\
12: & \quad \text{end if} \\
13: & \quad \text{return } X_2
\end{align*}
\]

### 2.3. Student training

This stage used KD loss [31] to transform the capabilities of GE2E-ResNetSE into ASD-ResNetSE. KD loss is mainly composed of Kullback–Leibler divergence (KL) and NLL loss. KL was used to estimate the ability of the student model to learn from the output of the teacher model, while NLL loss was used to estimate the ability of the student model to learn the ground-truth spoof. The overall loss function is:

\[
L_{KD} = \gamma T^2 \times KL\left(\frac{O_s}{T}, \frac{O_t}{T}\right) + (1 - \gamma)L_{NLL}
\]

where \( O_s \) means the output of the student model, \( O_t \) means the output of the teacher model, \( L_{NLL} \) is the NLL loss between the prediction of students and ground truth classes, \( T \) is the parameter controlling the distillation temperature, and \( \gamma \) is the weight for balancing the contribution from the teacher and the ground truth class. After completing this stage, the output of ASD-ResNetSE will be used to measure the final model performance.

### 3. Experiment Setup

**Dataset and evaluation metrics.** All experiments follow the ASVspoof 2021 [6] settings, and were performed on the ASVspoof 2019 [7] (for validation) and ASVspoof 2021 (for evaluation) LA dataset. We only reported the 2021 results here. Training and development partitions of ASVspoof 2019 were used to construct the countermeasures’ system. The system was evaluated on the ASVspoof 2019 and ASVspoof 2021 evaluation sets. There were 7 spoofing categories, including bonafide, A01-04 spoofed by TTS, and A05-06 spoofed by VC. Meanwhile, all the audio files were labeled with speakers. The training set included a total of 20 speakers, while the development set includes 10 speakers not included in the training set. The dataset we used included a training set of 25,380 utterances, a development set of 24,856 utterances and an evaluation set of 181,566 utterances. Minimum tandem decision cost function (min t-DCF) [37] and equal error rate (EER) were used to evaluate the effectiveness of the countermeasure (CM) models.

**Waveform augmentation.** The number of utterances in the evaluation data set was much larger than that in the training or developing sets. Therefore, we used waveform augmentation to expand the training data to increase system robustness. First, we randomly selected music, voice or noise in MUSAN [38] and trimmed or padded it to the same length as the target utterance, and then added it to the target audio file to generate new audio. Next, we randomly selected audio from the RIR noise data [39] and convoluted it with the target audio to generate new audio for reverberation simulation of different room sizes. The training data of all models in the experiment were augmented using the above-mentioned on-the-fly methods.

**Training Details.** We extracted 40 dimensions log-Mel spectrogram with a 25 ms window size, a 10 ms hop size, and an FFT size set as 512 as the input while all audio files had a sample rate of 22,050 Hz. Following acoustic extraction, we applied instance normalization to the feature. We set \( \alpha = 3.0 \), \( \text{iter} = 5 \), \( \text{threshold} = 0.4 \in \text{AEG augmentation} \). The \( \alpha \) and \( \text{iter} \) are referred from the empirical value of [27]. We applied waveform augmentation and used the Adam optimizer during the end-to-end teacher and student model training. At the beginning, the learning rate was set to 0.0003, and every two epochs it will become 0.95 times the original. \( \gamma = 0.5 \), \( T = 5 \) is set to KD loss, which was used on the student model.

### 4. Results and Analysis

#### 4.1. Ablation Study

**GE2E.** We compared the performance of ResNetSE and GE2E-ResNetSE model in Table 1. The results show that GE2E pre-training reduces the min t-DCF score from 0.3143 to 0.3003, while the EER was also reduced from 5.78 to 5.10. GE2E pre-training enables the model to distinguish information of the same spoofing condition from the information of other spoofing conditions, which helped classify the spoofing classes by providing additional spoofing condition information. Rather than classifying all the data at once, GE2E enabled the classification of spoof and non-spoof starting from classifying a particular spoofing condition case, which was expected to have better results.

<table>
<thead>
<tr>
<th>Model</th>
<th>Loss</th>
<th>min t-DCF</th>
<th>EER</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNetSE</td>
<td>( L_{NLL} )</td>
<td>0.3143</td>
<td>5.78</td>
</tr>
<tr>
<td>GE2E-ResNetSE</td>
<td>( L_{GE2E} + L_{NLL} )</td>
<td>0.3003</td>
<td>5.10</td>
</tr>
</tbody>
</table>

Table 1: Influence of GE2E pre-training.

**AEG.** The results (B)(C)(D) in the upper part of the Table 2 shows that both active and static AEG improved the performance of GE2E-ResNetSE. In particular, the active method effectively reduced the min t-DCF from 0.3003 to 0.2869 and the EER from 5.10 to 4.59% through on-the-fly augmentation. This showed that adding model-weakness data to the dataset during training can help the model perceive the subtle differences inside the spoofing audio streams. From the perspective of data preparation, the active method can be better implemented by creating adversarial examples in real-time, whereas the static
method generated the whole dataset before training.

**Knowledge Distillation.** The lower half of Table 2 is the result of ASD-ResNetSE obtained by distillation of the corresponding teacher through the KD process. The result of (A’) is our knowledge distillation baseline, its teacher (A) did not use GE2E pre-training and adversarial fine-tuning. The teacher (B) of student (B’) used GE2E pre-training, but not adversarial fine-tuning. The teachers (C) and (D) of (C’) and (D’) are based on GE2E-ResNetSE and also use static AEG and active AEG to inject adversarial speaker class during fine-tuning respectively. Note that we don’t use AEG during the distillation process.

According to Table 2, (A’) gains 4.9\% min t-DCF and 16.4\% EER improvement after distillation. (C’) obtains 8.0\% min t-DCF and 29.9\% EER improvement combined with GE2E pre-training and static AEG fine-tuning, which outperforms baseline (A’). However, (D’) degrades (-1.1\%) min t-DCF and -3.7\% EER. In most distillation results, the performance of the student model did not decrease, but increased. Previous work [40] have found that there are subnetworks exist in original network can reach or exceed the original model performance. Wang [41] has tried to find such a subnetwork through KD. [41] The above result shows that static AEG is more helpful than active AEG to find a super subnetwork in the adversarial speaker distillation process.

### 4.2. Overall Performance

To further analyze overall performance, we select our best ASD-ResNetSE model (C’) and ResNetSE (A) and the other existing countermeasure models, such as RawNet2 [10], SE-ResNet18 [11], LFCC-LCNN [12], ECAPA-TDNN [13], ASSERT34 [14] and W2V2-AASIST [15]. The best ASD-ResNetSE model and GE2E-ResNetSE model were from Table 2. For a fair comparison, we only consider the single models instead of the fusion models. Figure 3 visualize the relation between the model sizes and their performance of min t-DCF, EER. Because SE-ResNet18 does not provide EER results, so we do not make a comparison here.

In Figure 3, we mainly compare three aspects. Firstly, ASD-ResNetSE not only outperforms most countermeasure models but also has only a 22.5\% model size of ResNetSE. Secondly, ASD-ResNetSE is more than 50\% min t-DCF lower than ASSERT34, which has a similar model size to ASD-ResNetSE. Moreover, the EER of ASD-ResNetSE is only about 20\% of the EER of ASSERT34. The above results demonstrate that ASD-ResNetSE can obtain a better trade-off between the model size and performance. Thirdly, W2V2-AASIST achieves state-of-the-art min t-DCF and EER, consisting of a self-supervised learning frontend wav2vec2.0 [42, 43] and a countermeasure backend AASIST [44]. However, its parameters are over 1200 megabytes, so this is not practical for using it on edge devices.

### 4.3. Model Size and Operands

We compared the size and multiply and accumulate operands (MACs) of several methods, shown in Table 3. ASD-ResNetSE, with only 0.90G MACs, had a significantly smaller model size than ResNetSE. As the model size, ASD-ResNetSE also had similar MACs with ASSERT34. Combining the results in Table 3 and Figure 3, ASD-ResNetSE stood out with its capacity, efficiency and effectiveness.

### 5. Conclusion

This paper is the first to explore the lightweight CM model for ASV and propose an adversarial speaker distillation method, which is an improved version of knowledge distillation method. In the evaluation phase of the ASVspoof 2021 Logical Access task, The ASD-ResNetSE trained by our porpoised adversarial speaker distillation, which reaches min t-DCF 0.2695 and EER 3.54\% with only used 22.5\% of parameters and 19.4\% of MACs of the original ResNetSE model. The experiment results demonstrate that ASD-ResNetSE stood out with its capacity, efficiency and effectiveness.
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7. References