Defending Your Voice: Adversarial Attack on Voice Conversion

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Abstract

Substantial improvements have been achieved in recent years in voice conversion, which converts the speaker characteristics of an utterance into those of another speaker without changing the linguistic content of the utterance. Nonetheless, the improved conversion technologies also led to concerns about privacy and authentication. It thus becomes highly desired to be able to prevent one’s voice from being improperly utilized with such voice conversion technologies. This is why we report in this paper the first known attempt to try to perform adversarial attack on voice conversion. We introduce human imperceptible noise into the utterances of a speaker whose voice is to be defended. Given these adversarial examples, voice conversion models cannot convert other utterances so as to sound like being produced by the defended speaker. Preliminary experiments were conducted on two currently state-of-the-art zero-shot voice conversion models. Objective and subjective evaluation results in both white-box and black-box scenarios are reported. It was shown that the speaker characteristics of the converted utterances were made obviously different from those of the defended speaker, while the adversarial examples of the defended speaker are not distinguishable from the authentic utterances.

Index Terms: voice conversion, adversarial attack, speaker verification, speaker representation

1. Introduction

Voice conversion aims to alter some specific acoustic characteristics of an utterance, such as the speaker identity, while preserving the linguistic content. These technologies were made much more powerful by deep learning [14, 15, 16, 17, 18], but the improved technologies also led to concerns about privacy and authentication. One’s identity may be counterfeited by voice conversion and exploited in improper ways, which is only one of the many deepfake problems observed today generated by deep learning, such as synthesized fake photos or fake voice. Detecting any of such artifacts or defending against such activities is thus increasingly important [1, 6, 7, 8, 9], which applies equally to voice conversion.

On the other hand, it has been widely known that neural networks are fragile in the presence of some specific noise, or prone to yield different or incorrect results if the input is disturbed by such subtle perturbations imperceptible to humans [10]. Adversarial attack is to generate such subtle perturbations that can fool the neural networks. It has been successful on some discriminative models [11, 12, 13], but less reported on generative models [14].

In this paper, we propose to perform adversarial attack on voice conversion to prevent one’s speaker characteristics from being improperly utilized with voice conversion. Human-imperceptible perturbations are added to the utterances produced by the speaker to be defended. Three different approaches, the end-to-end attack, embedding attack, and feedback attack are proposed, such that the speaker characteristics of the converted utterances would be made very different from those of the defended speaker. We conducted objective and subjective evaluations on two recent state-of-the-art zero-shot voice conversion models. Objective gender classification showed the converted utterances were significantly different from those produced by the defended speaker, which was then verified by subjective similarity test. The effectiveness of the proposed approaches was also verified for black-box attack via a proxy model closer to the real application scenario.

2. Related works

2.1. Voice conversion

Traditionally, parallel data are required for voice conversion, or the training utterances of the two speakers must be paired and aligned. To overcome this problem, Chou et al. obtained disentangled representations respectively for linguistic content and speaker information with adversarial training [1]; CycleGAN-VC used cycle-consistency to ensure the converted speech to be linguistically meaningful with the target speaker’s features [2]; and StarGAN-VC introduced conditional input for many-to-many voice conversion [3]. All these are limited to speakers seen in training.

Zero-shot approaches then tried to convert utterances to any speaker given only one example utterance without fine-tuning, and the target speaker is not necessarily seen before. Chou et al. employed adaptive instance normalization for this purpose [4]; AUTOVC integrated a pre-trained d-vector and an encoder bottleneck, achieving the state-of-the-art results [5].

2.2. Attacking and defending voice

Automatic speech recognition (ASR) systems have been shown to be prone to adversarial attacks. Applying perturbations on the waveforms, spectrograms, or MFCC features was able to make ASR systems fail to recognize the speech correctly [15, 16, 17, 18, 19]. Similar goals were achieved on speaker recognition by generating adversarial examples to fool automatic speaker verification (ASV) systems to predict that these examples had been uttered by a specific speaker [20, 21, 22]. Different approaches for spoofing ASV were also proposed to show the vulnerabilities of such systems [23, 24, 25]. But to our knowledge, applying adversarial attacks on voice conversion has not been reported yet.

On the other hand, many approaches were proposed to defend one’s voice when ASV systems were shown to be vulnerable to spoofing attacks [25, 26, 27, 28, 29]. In addition to a challenge of ASVspoof for many years investigating such spoofing techniques and countermeasures [30], Liu et al. conducted adversarial attacks on those countermeasures, showing the fragility of them [20]. Obviously all neural network models are under the threat of adversarial attacks [11], which led to the

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3. Methodologies

A widely used model for voice conversion adopted an encoder-decoder structure, in which the encoder is further divided into a content encoder and a speaker encoder, as shown in Fig. 1. This paper is also based on this model. The content encoder $E_c$ extracts the content information from an input utterance $t$ yielding $E_c(t)$, while the speaker encoder $E_s$ embeds the speaker characteristics of an input utterance $x$ as a latent vector $E_s(x)$, as in the left part of Fig. 1. Taking $E_c(t)$ and $E_s(x)$ as the input, the decoder $D$ generates a spectrogram $F(t, x)$ with content information based on $E_c(t)$ and speaker characteristics based on $E_s(x)$.

Here we focus on the utterance $x$ whose speaker is not to be defended, while do not care the utterance $t$ offering the content, since the content can be re-uttered by arbitrary speakers then used in voice conversion. Motivated by the prior work [14], we present three approaches to perform the attack, with the target being either the output spectrogram $F(t, x)$ (Sec. 3.1), or the speaker embedding $E_s(x)$ (Sec. 3.2), or the combination of the two (Sec. 3.3), also shown in Fig. 1.

3.1. End-to-end attack

A straightforward approach to perform adversarial attack on the above model in Fig. 1 is to take the decoder output $F(t, x)$ as the target, referred to as end-to-end attack also shown in Fig. 1. Denote the original spectrogram of an utterance $x$ as a latent vector $E_s(x)$ and the adversarial perturbation on $x$ as $δ \in \mathbb{R}^M \times T$, where $M$ and $T$ are the total number of frequency components and time frames respectively. An untargeted attack simply aims to alter the output of the voice conversion model and can be expressed as:

$$\begin{align*}
\text{maximize} & \quad \mathcal{L}(F(t, x + δ), F(t, x)) \\
\text{subject to} & \quad ∥δ∥_{∞} < \epsilon
\end{align*}$$

(1)

$\mathcal{L}(\cdot, \cdot)$ is the distance between two vectors or the spectrograms for two signals and $\epsilon$ is a constraint making the perturbation subtle. The signal $t$ can be arbitrary offering the content of the output utterance, on which we do not focus here.

Given a certain utterance $y$ produced by a target speaker, we can formulate a targeted attack for output signal with specific speaker characteristics:

$$\begin{align*}
\text{minimize}_{\delta} & \quad \mathcal{L}(F(t, x + δ), F(t, y)) - \lambda \mathcal{L}(F(t, x + δ), F(t, x)) \\
\text{subject to} & \quad ∥δ∥_{∞} < \epsilon
\end{align*}$$

(2)

The first term in the first expression in (2) aims to make the model output sound like being produced by the speaker of $y$, while the second term is to eliminate the original speaker identity in $x$. $\lambda$ is a positive valued hyperparameter balancing the importance between source and target.

To effectively constrain the range of perturbation within $[-\epsilon, \epsilon]$ while solving (2), we adopt the approach of Change of variable as was done previously [11] using $\tanh(\cdot)$ function. In this way (2) above becomes (3) below:

$$\begin{align*}
\text{minimize}_{w} & \quad \mathcal{L}(F(t, x + δ), F(t, y)) - \lambda \mathcal{L}(F(t, x + δ), F(t, x)) \\
\text{subject to} & \quad δ = ε \cdot \tanh(w)
\end{align*}$$

(3)

where $w \in \mathbb{R}^{M \times T}$. The clipping function is not needed here.

3.2. Embedding attack

The speaker encoder $E_s$ in Fig. 1 embeds an utterance into a latent vector. These latent vectors for utterances produced by the same speaker tend to cluster closely together, while those by different speakers tend to be separated apart. The second approach proposed here is focused on the speaker encoder by directly changing the speaker embeddings of the utterances, referred to as embedding attack also in Fig. 1. As the decoder $D$ produces the output $F(t, x)$ with speaker characteristics based on the speaker embedding $E_s(x)$ as in Fig. 1, changing the speaker embeddings therefore alters the output of the decoder.

Following the notations and expressions in (3), we have:

$$\begin{align*}
\text{minimize}_{w} & \quad \mathcal{L}(E_s(x + δ), E_s(y)) - \lambda \mathcal{L}(E_s(x + δ), E_s(x)) \\
\text{subject to} & \quad δ = ε \cdot \tanh(w)
\end{align*}$$

(4)

where the adversarial attack is now performed with the speaker encoder $E_s$ only. Since only the speaker encoder is involved, it is therefore more efficient.

3.3. Feedback attack

The third approach proposed here tries to combine the above two approaches by feeding the output spectrogram $F(t, x + δ)$
from the decoder $D$ back to the speaker encoder $E_s$ (the red feedback loop in Fig. 1), and consider the speaker embedding obtained in this way. More specifically, $E_s(x + \delta)$ in (4) is replaced by $E_s(F(t, x + \delta))$ in (5). This is referred to as the feedback attack also in Fig. 1.

$$\min_{w} \mathcal{L}(E_s(F(t, x + \delta)), E_s(y)) - \lambda \mathcal{L}(E_s(F(t, x + \delta)), E_s(x))$$

subject to $\delta = \epsilon \cdot \tanh(w)$

(5)

4. Experimental settings

We conducted experiments on the model proposed by Chou et al. 6 (referred to as Chou’s model below) and AUTOVC. Both were able to perform zero-shot voice conversion on unseen speakers given their few utterances without fine-tuning, considered suitable for our scenarios.

4.1. Speaker encoders

For Chou’s model, all modules were trained jointly from scratch on CSTR VCTK Corpus 32. The speaker encoder took a 512-dim mel spectrogram and generated a 128-dim speaker embedding. AUTOVC utilized pre-trained d-vector 33 as speaker encoder, with 80-dim mel spectrogram as input and 256-dim speaker embedding as output, pre-trained on VoxCeleb1 34 and LibriSpeech 35 but generalizable to unseen speakers.

4.2. Vocoders

In inference, Chou’s model leveraged Griffin-Lim algorithm 36 to synthesize the audio. AUTOVC previously adopted WaveNet 37 as the spectrogram inverter, but here we used WaveRNN-based vocoder 38 pre-trained on VCTK corpus to generate waveforms with similar quality due to time limitation.

As we introduced perturbation on spectrogram, vocoders converting the spectrogram into waveform were necessary. We respectively adopted Griffin-lim algorithm and WaveRNN-based vocoder for attacks on Chou’s model and AUTOVC.

4.3. Attack procedure

We selected $L_2$ norm as $\mathcal{L}(. . )$, and $\lambda = 0.1$ for all experiments. Adam optimizer was adopted to update perturbations iteratively within a fixed number of iterations.

In white-box scenario, publicly available parameters were used. For black-box scenario, we trained another model with the same structure but different initialization. Attacks were performed on these newly trained models, while evaluated on publicly available ones. So all evaluation results were obtained with publicly available models.

5. Results

5.1. Objective tests

Although an intuitive assessment of the results here is speaker classification or verification over the converted utterances, we adopted gender classification accuracy as a more reliable and stronger metric, and the machine can estimate it more accurately. This is because if the gender was estimated by machine as different from the defended speaker, the speaker characteristics are definitely seriously altered, or the voice was well defended. The gender classification model used consisted of a pre-trained d-vector plus two fully-connected layers, with the last layer producing the gender prediction. It was trained on VCTK corpus, achieving over 99% accuracy on the validation set. We created 100 adversarial examples $(x + \delta)$ in (2) for 50 male and 50 female randomly selected speakers in VCTK corpus, targeting speakers with gender opposite to the defended speaker, and performed gender classification respectively on these adversarial example utterances (referred to as adversarial input), the converted utterances $F(t, x + \delta)$ (referred to as adversarial output), and the converted authentic utterances $F(t, x)$ as well (referred to as original output). The same examples were used in each test for Chou’s and AUTOVC.

Table I lists the gender classification accuracy for the defended speaker under white-box scenario. Results for the three approaches mentioned in Sec. 3 are in the three columns (i) (ii) (iii). Section (i) is for Chou’s model with rows (a) (b) respectively for adversarial input and adversarial output, while row (c) for original output. Similarly in section (II) for AUTOVC. We can see the adversarial inputs sounded very close to the defended speaker or the perturbation $\delta$ almost imperceptible (rows (a) (d) close to 1.00), while the converted utterances sounded as from an opposite gender (rows (b) (e) much lower). All three approaches were effective (rows (a) (b) (d) (e)), although end-to-end attack worked very well for Chou’s (row (b) and column (i)), while embedding attack worked very well for both Chou’s and AUTOVC with respective to both adversarial input and output (rows (a) (b) (d) (e) and column (ii)).

Table 1: Gender classification accuracy for the defended speaker with (I) Chou’s ($\epsilon = 0.1$) and (II) AUTOVC ($\epsilon = 0.05$) by the three proposed approaches under the white-box scenario.

| Utterances                  | Methodologies (white-box) |
|-----------------------------|---------------------------|
|                             | (i) | (ii) | (iii) |
| (I)                         |     |     |      |
| (a) adversarial input       | 0.84| 0.94| 0.93 |
| (b) adversarial output      | 0.28| 0.36| 0.35 |
| (c) original output         | 1.00| 1.00| 1.00 |
| (II)                        |     |     |      |
| (d) adversarial input       | 1.00| 0.97| 1.00 |
| (e) adversarial output      | 0.77| 0.60| 0.82 |
| (f) original output         | 0.88| 0.88| 0.88 |

For black-box scenario, we analyzed the same gender classification accuracy as in Table I for Chou’s model only but with varying scale of the perturbations $\epsilon$, with results plotted in Fig. 2 (a) (b) (c) respectively for the three approaches proposed. We see when $\epsilon = 0.1$ the adversarial inputs were kept almost intact (blue curves close to 1.0) while adversarial outputs were seriously disturbed (red curves much lower). However, as $\epsilon \geq 0.2$ the speaker characteristics of the adversarial inputs were altered drastically (blue curves went down), although the adversarial outputs sounded very different (red curves went very low).

Fig. 2 shows the same results as in Fig. 1 except on AUTOVC with embedding attack only (as the other two methods did not work well in white-box scenario in Table I row (e)). We see very similar results and the embedding attack could successfully attack AUTOVC.

Among the three proposed approaches, the embedding attack turned out to be the most attractive, considering both defending effectiveness and time efficiency. The feedback attack offered performance comparable to the embedding attack on Chou’s model, but less effective on AUTOVC. It also took more time to apply the perturbation as one more complete encoder-to-decoder inference was required. The end-to-end attack was less attractive in Table I (lower in row (a) and column (i) for Chou’s and higher in row (e) and column (i) for AUTOVC),
probably because the distance between spectrograms used here was not always parallel to the distance between speaker gender characteristics. The speaker embeddings used in the two other approaches (columns (ii) (iii)) worked better in this sense.

5.2. Subjective tests

The above gender classification was objective but not necessarily adequate. So we performed subjective evaluation but with the most attractive embedding attack on AUTOVC only for both white- and black-box scenarios. We manually selected 50 examples successfully converted by AUTOVC additionally. The corresponding adversarial inputs and outputs and the original outputs as used above were then created for each of these examples for \( \epsilon = 0.075 \). The subjects were then asked if the two given utterances were from the same speaker: one is the original utterance, whereas the other is the adversarial input, adversarial output, or original output. Each pair of utterances was evaluated by 5 subjects, and the results are bars (a) (b) for white-box, (c) (d) for black-box scenarios, and (e) for original output in Fig. 4. We can see at least 44% - 58% of the adversarial inputs preserved the original speaker characteristics very well (red in bars (a) (c)), yet at least 58% - 88% of the adversarial outputs were obviously considered from a different speaker (blue in bars (b) (d)). The black-box scenario is more difficult than the white-box one, but the approach is still effective to a good extent. The demo can be found at https://yistlin.github.io/attack-vc-demo

6. Conclusions

Improved voice conversion techniques imply higher demand for new technologies to defend personal speaker characteristics. This paper presents the first known attempt to try to perform adversarial attack on voice conversion. Three different approaches are proposed and tested on two state-of-the-art voice conversion models in both objective and subjective evaluation with very encouraging results, including for the black-box scenario closer to real applications.

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