Speaker anonymization: current methods, challenges and perspectives

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Outline

1. Intro to the task & VoicePrivacy Challenge 2024
2. Current directions in speaker anonymization
3. ...and current challenges
4. Conclusions
Part 1

Speaker anonymization
Speaker anonymization in a nutshell

Process a waveform to:
- Conceal speaker identity
- Preserve linguistic content
- Preserve other paralinguistic aspects (e.g. "emotional" content)

Output should also be a waveform.
Speaker anonymization in a nutshell

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**Note**: the attacker is “semi-informed” (they know the anon. system and use it to re-train the ASV model)
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VoicePrivacy Challenge (VPC) 2024

- Speaker anonymization competition
- Participants invited to design their own speaker anonymization system
- Ranked based on the presented metrics
- Notable changes w.r.t. 2022 edition:
  - Past para-linguistic preservation metrics: pitch correlation and voice distinctiveness
  - Every utterance anonymized independently: no fixed speaker → pseudo-speaker link ("utterance-level anon")
    - When the link is fixed (like in 2022): "speaker-level anon"
Part 2

Current directions in speaker anonymization
Current directions

- Voice conversion via x-vector manipulation
- Transcription-based methods (aka. STTTS)
- Methods based on discrete audio units
Voice conversion via x-vector manipulation

- Extraction of
  - F0 curve (voice pitch per time frame)
  - “bottleneck”/“linguistic” features (encode spoken content: embeddings of ASR model)
  - deep speaker embedding vector (a.k.a. “x-vector”)
- “Anonymization function” perturbs the x-vector in some way
- Vocoder uses these concatenated features to synthesize a new voice
Voice conversion via x-vector manipulation

Two recent examples (seen at ICASSP 2024)

● *Language-independent speaker anonymization using orthogonal Householder neural network* (Miao et al.)
  ○ Learns a parametric function that maximizes distance between $X_O$ and $X_p$, while preserving the overall distribution of x-vectors

● *Modeling pseudo-speaker uncertainty in voice anonymization* (Chen et. al)
  ○ Pseudo-speaker embedding is sampled from a gaussian distribution learned for each speaker
Voice conversion via x-vector manipulation

- “Vanilla” way
- Effective when the attacker is unable to reproduce the anonymization function
  - Makes it more difficult for attacker to train adversarial ASV system, resulting in increased privacy
- Conversely, a very “reproducible” function is bad
Transcription-based methods

- Erase speaker-specific info from bottleneck features by transcribing utterance (to the word or phoneme level)
- Waveform synthesis TTS-style
- “speech-to-text-to-speech” (STTTS)
- “Inject back” some information (e.g. F0 values after some random masking)
Transcription-based methods

**Example:** VPC baseline B3 from *Prosody Is Not Identity: A Speaker Anonymization Approach Using Prosody Cloning* (Meyer et al., ICASSP 2023)

Diagram from *The VoicePrivacy 2024 evaluation plan*
Transcription-based methods

- Strong information bottleneck induced by the transcription: high privacy protection
  - But other desired information could be lost (intonation, emotion)
  - TTS module must be conditioned to preserve that information

Utility VS privacy scores in VPC 2022

T04: transcription-based
Using discrete audio units

- Attempt to limit the amount of speaker information in linguistic features by quantizing them to discrete units
- Just another “information bottleneck”, not as extreme as STTTS
- Tradeoff between privacy and utility
  - Can depend on codebook size

Diagram from www.mqasem.net
Using discrete audio units

Example 1: VPC 2024 baseline B5 from Anonymizing Speech: Evaluating and Designing Speaker Anonymization Techniques (Champion, PhD dissertation, 2023)

Learned codebook like in a VQ-VAE

(Neural discrete representation learning, van den Oord et al., NeurIPS 2017)

Diagram from The VoicePrivacy 2024 evaluation plan
Using discrete audio units

Example 2: VPC 2024 baseline B4 from *Speaker anonymization with neural audio codec language models* (Panariello et al., ICASSP 2024)
Part 3

Current challenges in speaker anonymization
Evaluating spk anon is hard!
From a purely **technical** perspective:

- The task itself involves synthesis
- Several datasets to handle
- Several metrics to compute
- Privacy metric involves re-training a model: bugs/mistakes in doing that can result in overestimated privacy scores
Evaluating anonymization

Evaluating spk anon is hard!

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- **Word Error Rate (WER) ↓** Evaluates linguistic preservation
- **Unweighted average recall (UAR) ↑** Evaluates emotion preservation
- **Equal Error Rate (EER) ↑** Evaluates privacy protection
- **Automatic Speech Recognition (ASR)**
- **Speech Emotion Recognition (SER)** (on yet another dataset)
- **Anonymized data (trials)**
- **Automatic Speaker Verification (ASV) trained on anon. data**
- **Anonymized data (enrolls)**
- **Anonymization System**
- **Defender side**
- **Attacker side**
- **Anonymization System**
Evaluating anonymization

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Anonymized data (trials)

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Attacker side

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Speech Emotion Recognition (SER)
Evaluating anonymization

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From a purely technical perspective:

- The task itself involves synthesis
- Several datasets to handle
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- Privacy metric involves re-training a model: bugs/mistakes in doing that can result in overestimated privacy scores (I speak out of experience...)
Evaluating anonymization

And from a **conceptual** perspective:

- Do the metrics reflect real use cases?
  - E.g. subjective intelligibility and WER not strongly correlated (Pearson correlation: 0.14)
- Evaluating privacy protection requires impersonating the role of an attacker
  - But we do not know “the optimal attack”
  - ...what do we actually know?
Evaluating anonymization

About the “attacker”

- Even simple algorithms (e.g. DSP-based ones) are effective against “uninformed” humans
Evaluating anonymization

About the “attacker”

- Even with an ASV system, attacker has to have access to the anonymization system to be a real threat
  - Original enrollment VS anon. trials (O-A) close to 50% EER even for simpler systems
- Task “solved” for practical scenarios?

Privacy score (ASV EER, %) on Libri-dev Male of VPC24 baselines B1, B2, B4 under different attack scenarios
Evaluating anonymization

About the “attacker”

- Adversarial ASV must be retrained, but how?
  - More diversity in the training helps [1]: change spk → pseudo-spk mapping for every training sample (utterance-level anon)
    - But this depends on the anonymization function $a(\cdot)$... different for every system, less comparable results
  - Using same pseudo-spk for all data (“any-to-one”) would overcome this problem [2]
    - But quite unrealistic

Evaluating anonymization

... and about the “defender”!

- Speaker anonymization systems are complicated
  - Ablation studies require generating multiple anonymized datasets, can be costly
- How much personal information does each block of the system erase, exactly?
Evaluating anonymization

The “x-vector pool” anon. function: find 200 farthest embeddings from $X_o$, pick 100 at random, average into $X_p$.
If used: most of the anonymization actually takes place within the vocoder, not the anonymization module [3]...

“If we remove anon. module and do any-to-one pseudo-speaker, aren’t we just doing voice conversion?”

- Well... kind of
- A lot of ideas can be taken from the voice conversion community
  - We just have not done it that much... yet
- Overall, the goals differ:

<table>
<thead>
<tr>
<th>Objective</th>
<th>Metrics</th>
</tr>
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<tbody>
<tr>
<td><strong>Voice Conversion</strong></td>
<td>Recording of source speaker should sound like specific target speaker</td>
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<tr>
<td></td>
<td>“Speaker similarity”</td>
</tr>
<tr>
<td></td>
<td>MOS or other subjective metrics</td>
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<tr>
<td></td>
<td>WER/CER</td>
</tr>
<tr>
<td><strong>Speaker Anonymization</strong></td>
<td>Recording of source speaker should NOT sound like source speaker</td>
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<td></td>
<td>Specifically trained adversarial ASV model</td>
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<td></td>
<td>WER</td>
</tr>
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<td></td>
<td>Some utility metric...</td>
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</table>
Which utility metric? The use case matters

- Aside from WER, the actual utility metric depends on the task
- VPC rules attempt a general “one-size-fits-all” approach to utility:
  - 2022: WER + F0 curve preservation + variety of pseudo-spk voices (plus the subjective evaluation)
  - 2024: WER + emotion preservation
- Specific use cases might have different requirements
  - Downstream task fixed → No need to go back to waveform?
  - Anonymization needs to be evident → Better if speech does NOT sound natural?
  - What matters is only the spoken content → ...just transcribe it?
- VoicePrivacy proposes a general protocol, but it can be adapted!
How do we find practical use cases though?

- More dialogue with the legal community would be beneficial
  - Find out if, when and how anonymization actually matters from a legal standpoint
  - So that you don’t end up like me at ICASSP (or in many other situations):

  - This anonymization thing sounds cool, but why do we need it?
  - ...something something GDPR?
Part 4

Conclusion
To recap...

- Introduced speaker anonymization
  - Take a speech waveform
  - Mask the speaker identity
  - Preserve the rest
- Presented VoicePrivacy Challenge 2024 *(deadline: 15th of June)*
- Main research directions
  - Voice conversion based on x-vector manipulation
  - Transcription-based (STTTS)
  - Quantized speech units
- Current challenges
  - Both privacy and utility difficult to evaluate
  - Deal with an intrinsically “vague” task
Thank you!