Audio Codec Augmentation for Robust Collaborative Watermarking of Speech Synthesis

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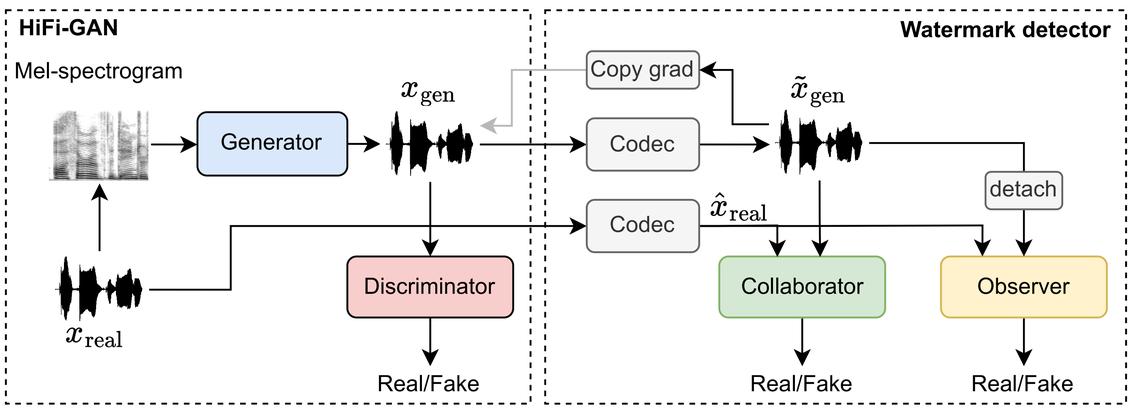
Introduction

- Text-to-speech tools with voice-cloning capability are widely available as open-source distributions or commercial services.
- Research on audio deepfake detection focuses mostly on passive protection using machine learning methods, which is also referred to as **speech anti-spoofing**.
- EU AI Act (article 50) will require marking AI-generated content
- Can speech synthesis take **active measures** to make synthetic speech easier to detect?

Watermarking for generative models

- Watermark requirements include **perceptual transparency**, **capacity**, **computational cost**, and **robustness**.
- Typical watermarking methods are separate from generative methods, and the watermark is applied as post-processing.
- In open-source settings, separate watermarks are often trivial to disable.
- **Detection can be seen as a zero-bit watermark**

Collaborative watermarking



A Generator model takes a mel-spectrogram as input and outputs a corresponding synthetic speech waveform. Detector models all try to classify between real and generated speech, and the training dynamics change based on which role the classifier takes:

1. **Discriminator** is adversarial to the Generator. The Generator attempts to fool the discriminator into classifying generated samples as real.
2. **Observer** acts as a passive detector. Gradient flow from the Observer to Generator is detached. This corresponds to traditional ASVspoof countermeasure training.
3. **Collaborator** shares its objective with the Generator. The pair attempt to discover a *watermark* that is embedded into the generated signal to aid in the binary classification task, while not hindering Generator's other objectives.

Experimental setting

- Generator and Discriminator are from HiFi-GAN, fine-tune a pre-trained model
- Detector is AASIST, fine-tune a pre-trained model
- Use straight-through estimator to get gradients for classic codecs (MP3 and OPUS) and DAC as a neural audio codec

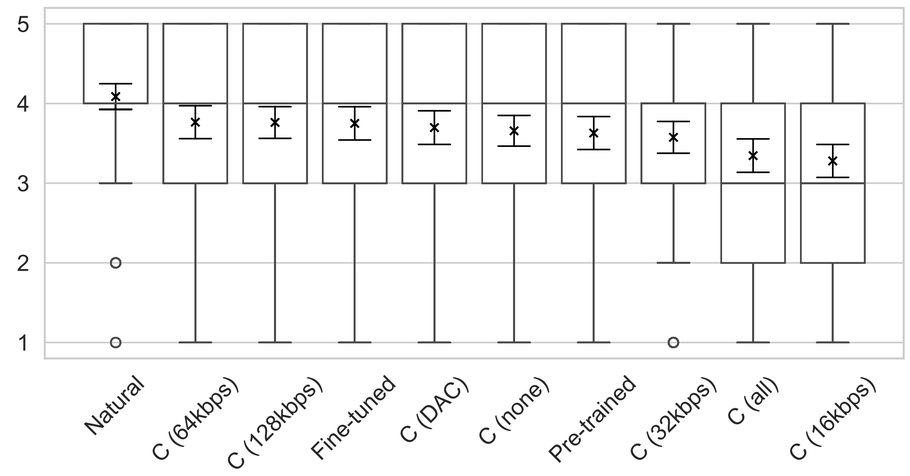
Results

How and what to read in the results table

- Detection Equal Error Rate (EER), don't look at the numbers, **look at the color**
- Columns are training conditions, Rows are test conditions
- More compression is challenging, look at rows with same codec at different rates
- Collaborative training helps, look at neighboring columns marked *o* for Observer and *c* for Collaborator
- Augmentation helps, compare the None column to various codec augmentation columns

Listening test

- Evaluate quality of clean vocoded speech using a mean opinion score (MOS) test
- Observer models correspond to fine-tuning the generator, augmentation has no effect by definition
- Collaborative detection through codecs has no significant quality impact at high bitrates and DAC
- Quality degrades when the model attempts to be robust at lower rate codecs
- With multiple bitrates quality is determined by the worst case (lowest bitrate)



Conclusions

- Actively making generated speech easier to detect can be viewed as zero-bit watermarking
- Augmentation with audio codecs improves detection robustness
- Collaborative training improves detection performance over passive Observer training
- Augmentation at high bitrates does no cause significant quality drop
- DAC augmentation generalizes surprisingly well to other codecs

Audio samples and source code

Source code and models
`https://github.com/ljuvela/collaborative-watermarking-with-codecs`

Sound samples
`https://ljuvela.github.io/collaborative-watermarking-with-codecs-demo/`

Augmentation tool
`https://github.com/ljuvela/DAREA`

codec		None		DAC		MP3/Opus									
	bitrate	-		8		16		32		64		128		all	
		o	c	o	c	o	c	o	c	o	c	o	c	o	c
None	-	1.53±0.3	0.29±0.1	2.75±0.4	0.00±0.0	33.16±0.9	3.66±0.5	9.39±0.6	14.95±0.9	3.43±0.4	0.17±0.1	1.28±0.2	0.85±0.3	3.91±0.4	4.44±0.5
DAC	8	35.85±1.0	24.29±0.9	5.09±0.5	0.00±0.0	32.81±1.0	3.97±0.5	27.54±0.9	24.68±0.9	34.46±0.9	75.54±1.2	34.03±0.9	10.03±0.6	20.86±0.8	5.62±0.5
OGG-Opus	16	53.42±1.0	41.53±1.0	34.67±0.9	31.73±0.9	37.09±1.0	5.17±0.6	37.46±1.0	36.49±1.3	47.07±1.0	89.91±0.9	44.88±1.0	41.39±0.9	40.65±1.0	10.50±0.7
OGG-Opus	32	21.75±0.8	9.18±0.6	14.55±0.7	0.72±0.2	34.30±1.0	4.01±0.5	19.29±0.9	14.76±0.9	17.12±0.8	4.09±0.4	20.55±0.8	6.74±0.5	13.64±0.7	6.59±0.6
OGG-Opus	64	4.55±0.4	0.45±0.1	5.31±0.5	0.00±0.0	33.12±1.0	3.62±0.4	10.90±0.7	13.93±0.8	5.79±0.6	0.29±0.1	3.45±0.4	0.70±0.2	5.40±0.5	4.78±0.5
OGG-Opus	128	2.27±0.3	0.21±0.1	3.12±0.4	0.00±0.0	33.24±1.0	3.62±0.5	9.32±0.6	14.58±0.8	3.85±0.5	0.14±0.1	1.61±0.3	0.79±0.2	4.07±0.4	4.44±0.5
MP3	16	49.70±1.0	48.42±1.0	30.72±0.9	6.82±0.6	34.46±1.0	4.82±0.6	36.28±1.0	78.89±1.1	48.56±1.0	79.18±1.2	48.34±1.0	52.82±1.0	37.25±0.9	8.39±0.7
MP3	32	31.96±1.0	11.49±0.7	12.16±0.6	0.52±0.2	33.64±1.0	4.07±0.5	21.73±0.9	16.13±0.8	26.32±0.9	28.76±1.2	26.24±0.9	6.59±0.5	19.14±0.8	6.00±0.6
MP3	64	6.26±0.5	0.79±0.2	4.80±0.4	0.04±0.1	33.33±0.9	3.91±0.5	12.43±0.7	14.55±0.8	7.38±0.6	0.33±0.1	5.15±0.4	0.93±0.3	6.76±0.5	4.96±0.5
MP3	128	1.92±0.3	0.29±0.1	2.85±0.3	0.00±0.0	33.18±0.9	3.89±0.4	9.53±0.6	14.86±0.8	3.56±0.5	0.17±0.1	1.34±0.3	0.89±0.3	4.13±0.4	4.78±0.5
OGG-Vorbis	q=1	46.50±1.0	27.08±0.9	35.21±1.0	30.23±1.0	34.75±0.9	5.81±0.6	37.03±1.0	21.73±0.9	47.53±1.0	55.20±1.3	46.85±1.1	32.25±0.9	35.97±1.0	12.07±0.8
OGG-Vorbis	q=2	42.17±1.0	17.39±0.8	21.94±0.9	14.39±0.8	33.18±0.9	4.20±0.5	25.49±0.9	14.99±0.8	41.10±1.0	57.70±1.4	41.70±1.0	15.09±0.7	29.07±0.9	6.08±0.6
OGG-Vorbis	q=3	38.10±0.9	9.59±0.7	15.79±0.7	9.24±0.7	33.41±1.0	3.76±0.5	21.07±0.8	13.33±0.8	35.52±1.0	24.85±1.2	34.32±0.9	5.75±0.4	23.57±0.9	4.98±0.5
All	-	28.58±0.2	16.38±0.2	19.06±0.2	9.12±0.2	33.87±0.3	4.20±0.1	21.52±0.2	17.82±0.2	24.77±0.2	31.68±0.4	26.37±0.2	13.81±0.2	20.74±0.2	6.43±0.2

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