Speaker anonymisation using the McAdams coefficient

Jose Patino1, Natalia Tomashenko2, Massimiliano Todisco3, Andreas Nautsch1 and Nicholas Evans1

1EURECOM, Sophia Antipolis, France
2LIA, Avignon Université, France
1firstname.lastname@eurecom.fr, 2firstname.lastname@univ-avignon.fr

Abstract

Anonymisation has the goal of manipulating speech signals in order to degrade the reliability of automatic approaches to speaker recognition, while preserving other aspects of speech, such as those relating to intelligibility and naturalness. This paper reports an approach to anonymisation that, unlike other current approaches, requires no training data, is based upon well-known signal processing techniques and is both efficient and effective. The proposed solution uses the McAdams coefficient to transform the spectral envelope of speech signals. Results derived using common VoicePrivacy 2020 databases and protocols show that random, optimised transformations can outperform competing solutions in terms of anonymisation while causing only modest, additional degradations to intelligibility, even in the case of a semi-informed privacy adversary.

Index Terms: anonymisation, pseudonymisation, privacy, de-identification, automatic speaker recognition

1. Introduction

Recent years have seen an increase in privacy legislation. Much of it covers what is referred to as personally identifiable information (PII), e.g. biometric data such as speech [1, 2]. The community-led VoicePrivacy initiative [3] aims to foster progress in the development of anonymisation techniques that can be employed to conceal PII contained within speech signals.

The VoicePrivacy 2020 evaluation plan [4, Sec. 3.2] specifies four requirements for successful anonymisation solutions. They should: (i) produce a speech waveform; (ii) suppress speaker-specific information as much as possible; (iii) preserve intelligibility and naturalness; (iv) protect voice distinctiveness. Anonymised speech should degrade the reliability of automatic speaker recognition while preserving other aspects of speech, such as those relating to intelligibility and naturalness.

Two baseline anonymisation systems were made available to VoicePrivacy 2020 participants: (i) a primary baseline based upon state-of-the-art x-vector embeddings and neural waveform techniques [6]; (ii) a secondary baseline, inspired from the McAdams coefficient [7], consisting of well-known signal processing techniques [8]. The primary baseline is comparatively complex and requires substantial training data and computational resources. Based upon a simple contraction or expansion of pole locations derived using linear predictive coding (LPC), the secondary baseline requires no training data and is comparatively straightforward and efficient. While the primary baseline better suppresses speaker specific information [3] (requirement ii), the secondary baseline better preserves voice distinctiveness [5] (requirement iv).

The work reported in this paper aims to explore more thoroughly the potential of well-known signal processing techniques as a solution to the anonymisation problem, and to assess the real need for and benefit of more complex, demanding solutions. The paper reports our efforts to optimise the original McAdams-based solution and its adaptation to a more stochastic approach which affords better protection from reversibility. Longer-term, it is hoped that this work might expose opportunities to improve performance by combining the components or techniques used by each baseline solution.

The remainder of this paper is organised as follows. Related past work is described in Section 2. The proposed approach to anonymisation is introduced in Section 3. Experiments are reported in Section 4, while a discussion of findings, conclusions and ideas for future work are presented in Section 5.

2. Previous work

A popular synthetic sound generation techniques in the field of music signal processing is that of additive synthesis [11]. The technique is used to generate timbre through the addition of multiple cosinoidal oscillations:

\[ y(t) = \sum_{k=1}^{K} r_k(t) \cos(2\pi(kf_0)t + \phi_k) \]

(1)

where \( k \) is the harmonic index, \( r_k(t) \) is amplitude, \( \phi_k \) is the...
The angle $\phi$ of poles with a non-zero imaginary part are raised to the power of the McAdams coefficient $\alpha$ to provoke an expansion/contraction in frequency in its associated formant.

This technique bears similarities to other, well-known techniques in speech processing [12–13, 14–15, 16–17]. One example is vocal tract length normalization (VTLN) [18, 19]. Warping functions are applied to the spectral log amplitude of each speech frame to modify not just the envelope, as in our approach described in Section 3, but also the pitch. It can hence be argued that these approaches offer greater anonymisation strength and that our approach may then be inferior where identification is performed by human listeners. However, conversion of the pitch may be somewhat redundant if anonymisation is to be performed purely for the purposes of deceiving automatic approaches to identification which rarely use estimates of pitch or source/residual signals.

3. Anonymisation using the McAdams coefficient

Our approach to pseudonymisation is explained in this section. It is based upon the idea of applying a shift to the formant positions in a speech utterance, thereby adjusting the timbre or spectral envelope. Representations of the latter are often used in the front-end of an automatic speaker verification (ASV) system. Consequently, manipulations to the formant positions should degrade ASV reliability and hence provide some level of anonymisation. In our approach, the degree of formant shifting is controlled by the McAdams coefficient $\alpha$ as in (1). The principal ideas are outlined first, before we show the resulting system is applied to the anonymisation of speech signals.

3.1. Application to speech signals

We use the McAdams coefficient to manipulate the formant positions of speech signals at the frame level. The system described below is that which we proposed as the secondary baseline for the VoicePrivacy 2020 challenge. The process is illustrated in Figure 1. First, source-filter analysis is applied to each frame using linear predictive coding (LPC). The source or residual is set aside for later resynthesis, whereas filter coefficients are used to derive the set of pole positions. Real-valued pole positions (with zero-valued imaginary terms) are left unmodified, whereas complex-valued poles (with non-zero imaginary terms) are shifted according to the higher branch in Figure 1. The shift, applied via the same transformation in (1), operates on the angle between the positive real axis and the vector extending from the origin in the $z$-plane to the complex pole position. This angle corresponds to frequency, with the upper half of the unit circle (angle of $\pi$ radians) corresponding to the sampling frequency. The full set of complex-valued pole positions is shifted according to $\phi^\alpha$ resulting in either clockwise or counter-clockwise shifts in pole locations.

This result of this process is illustrated in the $z$-plane of Figure 2 where the blue circles indicate original pole locations and where other points indicate induced shifts. As shown, the shift is different for each pole in terms of both direction and the scale of the shift. For poles with an angle of $\phi < 1$ radian, the shift $\phi^\alpha$ is counter-clockwise for values of $\alpha < 1$. While not explored in this work, values of $\alpha > 1$ would induce shifts in a clockwise direction for values of $\phi < 1$ radian. Poles with an angle of $\phi > 1$ radians undergo shifts in the opposite directions. Lastly, the scale of the shift is dependent upon the gap between $\phi$ and $\phi = 1$ radian; the greater the gap, the greater the shift. Example shifts in pole positions are illustrated in Figure 2 for values of $\alpha < 1$ for values $\alpha \in \{0.9, 0.7, 0.5\}$.

An illustration of the result in terms of spectral envelope is shown in Figure 2. Four spectra are illustrated. The spectra illustrated by the solid blue line is the original speech spectrum whereas the others show the spectra after anonymisation for values of $\alpha \in \{0.9, 0.7, 0.5\}$. The nearer a pole to the arc of the unit circle (Figure 1), the more apparent the corresponding peak in the spectral envelope, with each pole and peak loosely corresponding to a speech formant. Given a sampling rate of 16 kHz (as for VoicePrivacy 2020 data), the value of $\phi = 1$ radian corresponds to a frequency of approximately 2.5 kHz. The shift in pole positions is hence in opposite directions for frequencies either side of this threshold and is either an expansion away from 2.5 kHz or a contraction towards it.

Returning to Figure 1, the set of new poles, including original real-valued poles and those modified according to the format shifting procedure, are then converted back to LPC coefficients. The latter are combined with the residual from the original speech signal and then used to resynthesise an anonymised speech frame in the time domain. The stream of speech frames, each treated according to the procedure described above, is then combined by means of a standard overlap and add (OLA) technique to produce the final anonymised speech signal.

3.2. Stochastic anonymisation

The original VoicePrivacy baseline used an arbitrary, fixed McAdams coefficient of $\alpha = 0.8$. Clearly, there is scope for optimisation since different values further away from $\alpha = 1$ will potentially induce greater shifts in the pole positions and should hence provide greater levels of anonymisation (higher EERs). However, better anonymisation will likely come at the expense of speech distortion, with the latter likely also causing degradation to intelligibility and naturalness. Accordingly, we report new work which aims to explore the trade off between these two competing objectives. We restrict the study to values of $\alpha < 1$. Casual listening tests showed that the use of values of $\alpha > 1$ resulted in less acceptable degradations to intelligibility.

Next, rather than using a fixed, deterministic value of $\alpha$, which implies that anonymisation is reversible, we sought to confirm that different values of $\alpha$ can produce different pseudo-
4. Experiments

This section describes the VoicePrivacy 2020 database used in this work, the metrics used for assessment, the different attack models or scenarios and our results.

4.1. Data and metrics

We used the VoicePrivacy 2020 database and protocols described in [3][4]. However, in contrast to the primary baseline [6][22], our anonymisation system has no requirement for training data. Consequently, our solution makes no use of the training partition. We report results for evaluation data only, which is drawn from the LibriSpeech [23] and VCTK [24] source datasets. While we have observed differences in performance for each dataset, as well as gender dependencies, for reasons of space limitations we report only average performance here. Database, gender dependencies and other potential biases, obviously warrant investigation in further work. Assessment is performed using the standard VoicePrivacy 2020 ASV and ASR systems [3] both trained using the train-clean-360 par-

Full results available at [https://github.com/josepatino/Voice-Privacy-Challenge-2020/blob/master/results/](https://github.com/josepatino/Voice-Privacy-Challenge-2020/blob/master/results/)

- Degradation to intelligibility is measured through the ASR word error rate (WER) whereas anonymisation performance is measured through the ASV equal error rate (EER). Also reported here are estimates of privacy using the zero evidence biometric recognition assessment (ZEBRA) framework [25], a recently proposed, adversary-agnostic, metric inspired by the work of the forensic sciences community.

4.2. Scenarios

In adopting the terminology of [21], we investigated anonymisation performance according to two different attack models or scenarios. Both involve a privacy adversary who seeks to determine whether two utterances belong, or not, to the same speaker. In both cases there is a test utterance which is anonymised, and an enrolment utterance which is either an original utterance, or a similarly-anonymised utterance.

The first scenario assumes an ignorant privacy adversary who has no knowledge of the test utterance being anonymised. In this case the adversary attempts to determine the match between an original enrolment utterance and an anonymised test utterance. This is referred to as the o-a scenario. The second scenario assumes a semi-informed privacy adversary who, while knowing that the test utterance has been anonymised and having access to the systems used, does not know the configuration. In this case, the adversary will likely determine more reliably the match between the two utterances by anonymising the enrolment utterance such that the comparison is now between two similarly anonymised utterances, even though each is anonymised with differently configured systems. It is referred to as the a-a scenario. Like [21], we do not consider the unlikely scenario of an informed adversary that has knowledge of both the algorithm and the configuration.

We also report ASV and ASR results derived from systems that are retrained on either original or anonymised data. These experiments aim to determine robustness in the case that the adversary is able to harness knowledge of the anonymisation system to break the protection it affords. Similarly, we seek to determine the improvements one can obtain in intelligibility, if the ASR system is adapted to anonymised data. See [4] for further details.

4.3. Results

Anonymisation results in terms of ASV EER are illustrated in Figure [5]. Results are shown for an original setup without anonymisation, for the primary and secondary VoicePrivacy 2020 baselines (B1 and B2) and for B2 stochastic variants where the McAdams coefficient is drawn from different...
intervals in $\alpha \in U(\alpha_{\text{min}}, \alpha_{\text{max}})$. All systems based on the McAdams coefficient have an LPC order of 20.

It is clear that all systems increase the EER from the original 3.3%. Blue, left-most bars show EERs for ignorant privacy adversaries (o-a scenario) when test utterances are anonymised but enrolment utterances are not. Results show that B1 outperforms B2 and all related systems by a substantial margin. Yellow, middle bars show performance for semi-informed privacy adversaries (a-a scenario) when both enrolment and test utterances are anonymised (with the same, but differently configured algorithm). Now, B2 and related systems are more competitive, e.g. 33.8% for U(0.7,0.9) cf. 32.5% for B1.

While lower values of $\alpha_{\text{min}}$ give better anonymisation, improvements are accompanied by degradations to intelligibility. ASR results for the same setups are illustrated in Figure 5. An original, baseline WER of 8.45% increases only to 10.95% for B1, but to 13.7% for U(0.8,0.9) and worse for other configurations. Thus, while the McAdams approach to anonymisation can better protect privacy, it does so at the cost of reduced intelligibility.

The question then is what level of improvement to intelligibility can be delivered simply by retraining the ASR systems with anonymised speech and what would be the corresponding impacts to ASV. Answers are provided by the green bars in Figures 4 and 5 for ASV and ASR systems respectively. For ASV, the McAdams approach to anonymisation performs best, e.g. 22.6% for U(0.8,0.9) cf. 13.7% for B1. Now, though, while better anonymisation is achieved for $\alpha_{\text{min}} < 0.8$, the corresponding WER is much more competitive with the degradation for B1. Whereas for the latter, the WER decreases from 10.95% to 8.25%, it decreases from 45% to 9.6% for U(0.5,0.9), while the EER is almost twice as high than for B1, e.g. up to 37.5% for U(0.5,0.9).

Table 1 shows ZEBRA results which reflect the evidence remaining to a privacy adversary after anonymisation. They correspond to the semi-informed scenario where the ASV system is retrained on anonymised data, i.e. the green bars in Figures 4 and 5. While the scales are inverted (less bits of disclosure infer better privacy), ZEBRA results shown in column 2 confirm much the same trend shown by EER results. Noting that anonymisation affords different levels of privacy to different individuals, the ZEBRA framework also allows one to determine the worst case level of privacy disclosure. According to [25], this is expressed according to categorical tags where a tag of ‘0’ reflects no privacy disclosure, ‘A’ is the next best case and where tag ‘F’ reflects the worst. Identical categorical tags of ‘C’ illustrated in column 3 for each system suggest that the differences in performance discussed above are not so great from the perspectives of a worst case scenario.

5. Conclusions

This paper shows that well-known signal processing techniques can provide efficient and effective solutions to anonymisation for speech signals. The approach reported in this paper, based upon transformations to the spectral envelope using the McAdams coefficient, can increase by ten-fold the equal error rate of a baseline automatic speaker recognition system, with only modest degradations to intelligibility, even in a semi-informed privacy adversary scenario. This is achieved with a randomised transformation which provides some level of protection from reversibility.

Despite this encouraging result, we must acknowledge that, until error rates increase to the equivalent of random performance, or a ZEBRA category of ‘0’, we remain far from meeting the goal of true anonymisation. Database, gender and other biases mean that an ‘averaged’ view of privacy tells an incomplete picture, especially when we know that even the stronger anonymisation solutions still leave some with relatively weaker protection. Encouragingly, there is plenty of scope to extend this work. Thus far we have considered only adjustments to the formant positions in terms of frequency. Future work should explore more elaborate transformations to the spectral envelope which could be investigated through random pole perturbations. There is also scope to explore the resilience of the approach to brute-force attacks, and new approaches which combine the merits of our approach with those of the more sophisticated VoicePrivacy primary baseline based upon state-of-the-art x-vector embeddings and neural waveform techniques.

Last, all results reported in this paper are reproducible with open source code and scripts available online.

6. Acknowledgements

This work is partly funded by the VoicePersonae project which is supported by the French Agence Nationale de la Recherche (ANR) and the Japan Science and Technology Agency (JST). It is also linked to the VoicePrivacy initiative and the Harpocrates project also funded by the ANR.

https://github.com/josepatino/ Voice-Privacy-Challenge-2020/
7. References

[1] A. Nautsch, C. Jasserand, E. Kindt, M. Todisco, I. Trancoso, and N. Evans, “The GDPR & speech data: Reflections of legal and technological communities, first steps towards a common understanding,” in Proc. INTERSPEECH, 2019.

[2] A. Nautsch, A. Jiménez, A. Treiber, J. Kolberg, C. Jasserand, E. Kindt, H. Delgado, M. Todisco, M. A. Hinani, A. Mubaa et al., “Preserving privacy in speaker and speech characterisation,” Computer Speech & Language, vol. 58, pp. 441–480, 2019.

[3] N. Tomashenko, B. M. L. Srivastava, X. Wang, E. Vincent, A. Nautsch, J. Yamagishi, N. Evans, J. Patino, J.-F. Bonastre, P.-G. Noé et al. “Introducing the VoicePrivacy initiative,” in Proc. INTERSPEECH, 2020.

[4] ——. “The VoicePrivacy 2020 Challenge evaluation plan,” 2020.

[5] P.-G. Noé, J.-F. Bonastre, D. Matrouf, N. Tomashenko, A. Nautsch, and N. Evans, “Speech Pseudonymisation Assessment Using Voice Similarity Matrices,” in Proc. INTERSPEECH, 2020.

[6] F. Fang, X. Wang, J. Yamagishi, I. Echizen, M. Todisco, N. Evans, and J.-F. Bonastre, “Speaker Anonymization Using X-vector and Neural Waveform Models,” in Proc. 10th ISCA Speech Synthesis Workshop, 2018, pp. 155–160.

[7] S. McAdams, “Spectral fusion, spectral parsing and the formation of the auditory image,” Ph. D. Thesis, Stanford, 1984.

[8] J. Patino, M. Todisco, A. Nautsch, and N. Evans, “Speaker anonymisation using the McAdams coefficient,” Eurecom, Tech. Rep. RR-20-343, 2020 [Online]. Available: http://www.eurecom.fr/publication/6190, Tech. Rep., 2020.

[9] P. Gupta, G. P. Prajapati, S. Singh, M. R. Kantble, and H. A. Patil, “Design of voice privacy system using linear prediction,” in Proc. APSIPA. IEEE, 2020, pp. 543–549.

[10] H. Kawai, S. Takamichi, S. Shiotani, and H. Kiya, "Lightweight voice anonymization based on data-driven optimization of cascaded voice modification modules," in Proc. IEEE SLT, 2021.

[11] C. Dodge and T. A. Jerse, Computer Music: Synthesis, Composition and Performance, 2nd ed. Macmillan Library Reference, 1997.

[12] Q. Jin, A. R. Toth, T. Schultz, and A. W. Black, “Speaker de-identification via voice transformation,” in Proc. ASRU. IEEE, 2009, pp. 529–533.

[13] M. Pobar and I. Ipšič, “Online speaker de-identification using voice transformation,” in 2014 37th International convention on information and communication technology, electronics and microelectronics (mipro). IEEE, 2014, pp. 1264–1267.

[14] F. Bahmaninezhad, C. Zhang, and J. H. Hansen, “Convolutional neural network based speaker de-identification.” in Proc. Odyssey, 2018, pp. 255–260.

[15] J. Qian, H. Du, J. Hou, L. Chen, T. Jung, X.-Y. Li, Y. Wang, and Y. Deng, “Voicemask: Anonymize and sanitize voice input on mobile devices,” arXiv preprint arXiv:1711.11460, 2017.

[16] C. Magarínos, P. Lopez-Otero, L. Docio-Fernandez, E. Rodriguez-Banga, D. Erro, and C. Garcia-Mateo, “Reversible speaker de-identification using pre-trained transformation functions,” Computer Speech & Language, vol. 46, pp. 36–52, 2017.

[17] B. M. L. Srivastava, A. Bellet, M. Tommasi, and E. Vincent, “Privacy-preserving adversarial representation learning in ASR: Reality or illusion?” arXiv preprint arXiv:1911.04913, 2019.

[18] J. Cohen, T. Kann, and A. G. Andreou, “Vocal tract normalization in speech recognition: Compensating for systematic speaker variability,” The Journal of the Acoustical Society of America, vol. 97, no. 5, pp. 3246–3247, 1995.

[19] L. Lee and R. Rose, “A frequency warping approach to speaker normalization,” IEEE Transactions on speech and audio processing, vol. 6, no. 1, pp. 49–60, 1998.

[20] J. Qian, H. Du, J. Hou, L. Chen, T. Jung, and X.-Y. Li, “Hide behind: Enjoy Voice Input with Voiceprint Unclonability and Anonymity,” in Proc. ACM Conference on Embedded Networked Sensor Systems, 2018, pp. 82–94.

[21] B. M. L. Srivastava, N. Vaquier, M. Sahidullah, A. Bellet, M. Tommasi, and E. Vincent, “Evaluating voice conversion-based privacy protection against informed attackers,” in Proc. ICASSP, IEEE, 2020, pp. 2802–2806.

[22] B. M. L. Srivastava, N. Tomashenko, X. Wang, E. Vincent, J. Yamagishi, M. Maouche, A. Bellet, and M. Tommasi, “Design choices for x-vector based speaker anonymization,” in Proc. INTERSPEECH, 2020.

[23] V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “Librispeech: an ASR corpus based on public domain audio books,” in Proc. ICASSP. IEEE, 2015, pp. 5206–5210.

[24] C. Veaux, J. Yamagishi, K. MacDonald et al., “CSTR VCTK corpus: English multi-speaker corpus for CSTR Voice Cloning Toolkit,” 2016.

[25] A. Nautsch, J. Patino, N. Tomashenko, J. Yamagishi, P.-G. Noé, J.-F. Bonastre, M. Todisco, and N. Evans, “The Privacy ZEBRA: Zero Evidence Biometric Recognition Assessment,” in Proc. INTERSPEECH, 2020.