PSVRF: LEARNING TO RESTORE PITCH-SHIFTED VOICE WITHOUT REFERENCE

Yangfu Li, Xiaodan Lin and Yingqiang qiu*

School of Information Science and Engineering, Huaqiao University, Xiamen, China

ABSTRACT

Pitch scaling algorithms have a significant impact on the security of Automatic Speaker Verification (ASV) systems. Although numerous anti-spoofing algorithms have been presented to identify the pitch-shifted voice and even restore it to the original version, they either have poor performance or require the original voice as a reference, limiting the prospects of applications. In this paper, we propose a no-reference approach termed PSVRF for high-quality restoration of pitch-shifted voice. Experiments on AISHELL-1 and AISHELL-3 demonstrate that PSVRF can restore the voice disguised by various pitch-scaling techniques, which obviously enhances the robustness of ASV systems to pitch-scaling attacks. Furthermore, the performance of PSVRF even surpasses that of the state-of-the-art reference-based approach.

***Index Terms*—** voice restoration, anti-sproofing, Automatic Speaker Verification (ASV), pitch scaling

1. INTRODUCTION

Motivation: The recent emergence of Automatic Speaker Verification (ASV) systems in high-security-required fields like AIoT, Voice Assistant, and multimedia forensics leads to an increasing concern about their security risks [1–3]. ASV systems utilize the distance between the extracted features of test speech and those of pre-collected reference speech to determine the speaker. However, the attackers could hide the real identity of a speaker through Automatic Voice Disguise (AVD). In particular, a classic AVD technique termed pitch scaling [4] is extensively applied in various commercial software due to the trade-off between effectiveness and efficiency of disguising, posing a great threat to ASV systems.

Prior works and limitaion: Early works [5–7] typically aim to estimate the approximate range rather than the precise degree of shifting pitch, rendering them incapable of accurately restoring the original voice. Later, Pilia et al. model the pitch-shifted voice detection as a regression problem to estimate disguising factors accuratly [8]. However, his method is limited to dealing with time-domain pitch scaling. Recently, L. Zheng et al. propose a state-of-the-art (SOTA) method for detecting pitch-shifted voices and restoring them to original revision [9]. This method constructs a series of pre-restorations by a pitch-scaling algorithm using different disguising parameters and utilizes an ASV system to seek the most similar one to the reference as the restoration result. It is capable of reliably working on various pitch scaling algorithms. However, it still has two limitations: (1) due to the dependency on the ASV system, it cannot be adaptive to the situation without reference speech; (2) pitch-scaling algorithms introduce unpleasant arctifacts into the pre-restoration, which leads to poor quality of the final restoration.

Our approach: In this paper, we propose a *Pitch-Shifted Voice Restoration Framework* (PSVRF) for estimating disguising parameters in the absence of reference and restoring pitch-shifted voice in high quality. Specifically, PSVRF consists of three contributing components: (1) Estimator, which predicts the disguising parameter through the log Mel filterbank (fbank) features of disguised voice without any reference; (2) Feature Reconstruction Network (FRN), which reconstructs the fbank features of original voice in high quality through fbank features of pitch-shifted voice and the predicted parameter; and (3) a neural vocoder, which converts the reconstructed features into waveforms, achieving end-to-end pitch-shifted voice restoration. The experiments conducted on AISHELL-1 and AISHELL-3 with various pitch scaling algorithms demonstrate that PSVRF overpasses the reference-based restoration method [9] in not only the accuracy of estimation but also the quality of restoration.

2. BACKGROUND

2.1. Pitch Scaling

Pitch scaling techniques can be mainlly divided into two categories: frequency-domain (FD) disguise and time-domain (TD) disguise. FD disguise is usually operated by expanding or compressing the spectrum while keeping the content of the voice unchanged. TD disguise can be realized by adjusting the sampling rate, which changes the fundamental frequency of speech signal and hence the pitch. FD disguise and TD disguise can be formulated into a unified form as follows [9]:

$$p_s = 2^{\alpha/12} p_o, \tag{1}$$

where p_o and p_s represent the original pitch and scaled pitch. α is the semitone, i.e., the diguising parameter, which describes the degree of disgusie.

Code is avaliable on: `https://github.com/YChenL/PSVRF`.

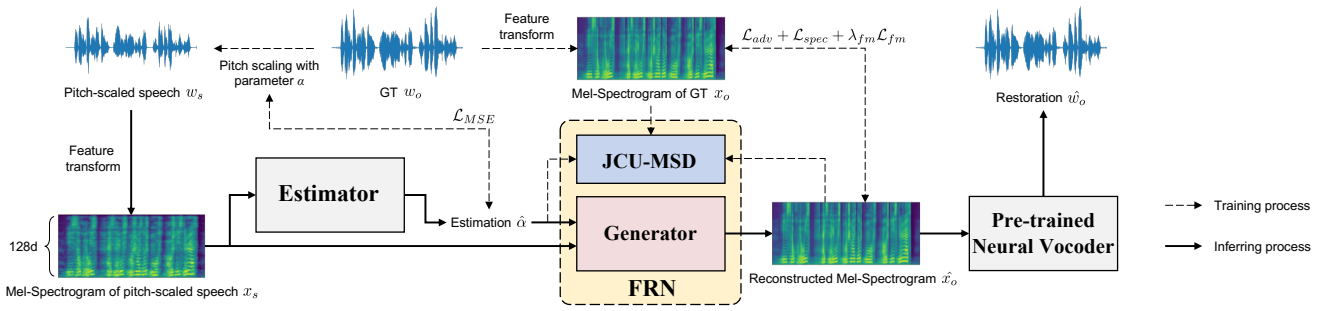


Fig. 1: Overview of PSVRF, which includes Estimator, FRN composed of a generator and the associated Joint Conditional-Unconditional Multi-scale Discriminator (JCU-MSD), and a neural vocoder.

2.2. Self-supervied audio spectrogram transformer

Audio sepctrogram transformer (AST) is the SOTA purely attention-based model for audio tasks [10]. Recently, K. He et al. propose Masked AutoEncoder (MAE) for a large-scale self-supervised pre-train [11], which can obviously enhance the performance of the purely attention-based model in vision. Specifically, it masks numerous patches of the inputs and then utilizes the model to reconstruct the masked inputs. Later, Y. Gong et al. introduce the pre-train strategy proposed in MAE into AST and propose the Self-supervied audio spectrogram transformer (Ssast) [12], which makes two efficient improvements: (1) a frame-level masking strategy, which is more efficient than patch-level masking; (2) Joint Discriminative and Generative Masked Spectrogram Patch Modeling.

3. METHODOLOGY

The architecture and objective functions of PSVRF are shown in Fig. 1, which consists of three main components: Estimator, FRN, and a Nerual Vocoder, achieving the restoration of pitch-shifted voice end-to-end. We detail these components in subsection **3.1** to **3.3**.

3.1. Estimator

Estimator is similar to the AST, which is composed of a linear projection and a transformer encoder. Specifically, each fbank feature is partitioned into 16×16 patches and flattened into 1D 768-dimensional patch embeddings, which are fed into the linear projection. Then, the transformer encoder accepts the output of the linear projection plus the position embedding as the inputs. The transformer encoder has an embedding dimension of 768, 12 layers, and 12 heads, which are the same as those in the original AST [10]. Finally, a global average pooling and a fully connected layer are applied to yield the estimation of the disgusing parameter according to the outputs of the encoder. Estimator is pre-trained in Voxceleb [13] and Voxceleb2 [14] with 400 epochs in the same way as Ssast and fine-tuned in a supervised mode using MAE loss.

3.2. Feature Reconstruction Network

FRN is designed to remove the artifacts introduced by disguising algorithms and recover the fbank feature of original speech. To be specific, FRN is a Generative Adversarial Network [15], which is composed of a generator G and the associated discriminator D_ϕ.

Architecture: As shown in Fig. 2 (a), G is mainly composed of 20 residual blocks with a hidden dimension of 256, which is introduced in WaveNet [16]. Differently, we make the model non-causal and set the dilation rate to 1 since the inputs are spectrograms instead of waveforms. Multi-scaled discriminators [17] and Joint Conditional Unconditional discriminators [18] have been proven effective in many audio tasks. Inspired by them, we propose a Joint Conditional Unconditional Multi-scale discriminator (JCU-MSD) D_ϕ, which is shown in Fig. 2 (b).

Objective function: Adversarial loss $\mathcal{L}_{adv}$, spectrogarm reconstruction loss $\mathcal{L}_{spec}$, and feature matching loss $\mathcal{L}_{fm}$ are applied to constrain the generator. $\mathcal{L}_{adv}$ is defined as follows:

$$\mathcal{L}_{adv} = \mathbb{E}_{x\sim x_o}[D_\phi(x,\hat{\alpha})^2] + \mathbb{E}_{x\sim G}[(D_\phi(x,\hat{\alpha})-1)^2], \quad (2)$$

where x_o is fbank feature of orginal speech. $\hat{\alpha}$ is estimated disguising parameters. $\mathcal{L}_{spec}$ is measured by L2 distances between the real spectrogram and its reconstructed counterpart, which can be formulated as follows:

$$\mathcal{L}_{spec} = ||x_o - G(x_s,\hat{\alpha})||_2, \quad (3)$$

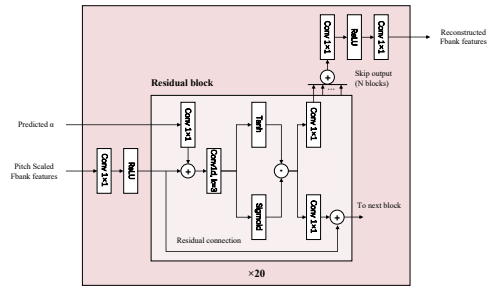
where x_s is fbank feature of digusied speech. $\mathcal{L}_{fm}$ is computed by summing L1 distances between every discriminator feature maps of real and generated samples, which is defined as follows:

$$\mathcal{L}_{fm} = \sum_{i=0}^{N} ||D_\phi^i(x_o,\hat{\alpha}) - D_\phi^i(G(x_s,\hat{\alpha}),\hat{\alpha})||_1, \quad (4)$$

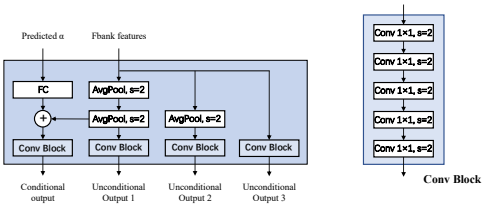
where N is the total number of hidden layers in the JCU-MSD. Finally, the total loss of PSVRF is defined as follows:

$$\mathcal{L}_{total} = \mathcal{L}_{adv} + \mathcal{L}_{spec} + \lambda_{fm}\mathcal{L}_{fm}, \quad (5)$$

where λ_{fm} is a scaled scalar equal to 0.5 in this work. G aims to minimize $\mathcal{L}_{total}$ while the objective of D is oppsite to G.



(a) Generator



(b) JCU-MSD

Fig. 2: Detailed structure of the generator and JCU-MSD, where Conv1 $\times$ 1 represents an one-dimensional (1D) convolutional operation with kernel size 1.

3.3. Neural Vocoder

We use the SOTA neural vocoder termed DiffWave [19] to transform the reconstructed fbank features into the restored waveform. This vocoder is pretrained in Voxceleb [13] and Voxceleb2 [14] with 10^6 steps and directly applied in PSVRF. Differently, the dimension of the input spectorgrams is set to 128 instead of 80 in this work.

4. EXPERIMENTS

4.1. Implement details

Dataset and processing: We utilize two multi-speaker mandarin datasets, AISHEEL-1 [20] and AISHELL-3 [21], to synthesize the training and test sets, which are shown in Table 1. To be specific, original training sets of AISHELL-1 and AISHELL-3 are resampled to 16kHz to construct two different scale datasets for training PSVRF, i.e., T1 and T2. Analogously, the test and validation sets of AISHEEL-1 and AISHELL-3 are also resampled and divided into two categories based on the visibility of contained speakers, which are used to build three test sets. Each of them is shuffled and divided into 33 subsets, and each subset is disguised using not only FD algorithms such as Phase Vocoder and FD-PSOLA but also TD algorithms such as TD-PSOLA and WSOLA. The disguising parameter α increases from -8 to 8 with a step of 0.5, yielding the A_1 Unseen, A_3 Seen, and A_3 Unseen. In addition, Audacity, Audition, and iZotope, three types of commercial audio processing software, are used to simulate more challenging and practical application scenarios.

Table 1: Speech attribute distribution

Denote	Dataset	Speakers	Utterances	α Range	Avg. Duration
T1	AISHELL-3 train	138 F/36 M	63262	$\mathcal{U}(-8,8)$	3.87 sec
T2	AISHELL-1 train	356 F/158 M	123471	$\mathcal{U}(-8,8)$	4.82 sec
	AISHELL-3 train				3.87 sec
A_1 Unseen	AISHELL-1 test	35 F/25 M	651 $\times$ 33	$[-8,8,0.5]$	4.36 sec
	AISHELL-1 dev				4.47 sec
A_3 Seen	AISHELL-3 test	134 F/36 M	270 $\times$ 33	$[-8,8,0.5]$	3.16 sec
A_3 Unseen	AISHELL-3 test	38 F/6 M	480 $\times$ 33	$[-8,8,0.5]$	

Table 2: MAE of estimated α, red is the best, blue is the second. ($\mathrm{PSVRF}_{\mathrm{T1}}$ / $\mathrm{PSVRF}_{\mathrm{T2}}$ / L. Zheng [9])

Implementation	A_1 Unseen	A_3 Seen	A_3 Unseen	Algorithm
librosa [22]	0.691 / 0.188 / 0.675	0.324 / 0.319 / 1.020	0.385 / 0.356 / 0.890	Phase Vocoder
MATLAB*	0.698 / 0.213 / 0.590	0.448 / 0.417 / 0.979	0.515 / 0.460 / 0.848	Phase Vocoder
RTISI [24]	0.771 / 0.661 / 0.684	0.961 / 0.929 / 0.939	0.982 / 0.946 / 0.952	FD-PSOLA
PRAAT	0.717 / 0.616 / 0.619	0.932 / 0.912 / 0.919	0.968 / 0.933 / 0.930	TD-PSOLA
SoundTouch [25]	0.753 / 0.543 / 0.607	1.249 / 1.161/ 0.880	1.251 / 1.162 / 0.929	WSOLA
Audacity 3.1.3	0.784 / 0.754 / 0.631	1.317 / 1.173 / 1.091	1.393 / 1.198 / 0.932	UNKNOWN
Audition 2022	0.767 / 0.402 / 0.586	1.112 / 1.076 / 0.927	1.272 / 1.202 / 0.956	UNKNOWN
iZotope RX9	0.828 / 0.476 / 0.575	1.445 / 1.311 / 0.983	1.644 / 1.465 / 0.974	UNKNOWN

* shiftPitch function.

Training setup: The pitch-scaling algorithm applied in training phase is Phase Vocoder implemented by `librosa` [22], where the disguising parameter α follows a uniform distribution $\mathcal{U}(-8,8)$. In Estimator the time dimension of the input is fixed to 500. In feature transform, the sampling rate is 16kHz, fft points are 1024, the window length is 1024, and the hop length is 256. The Adam optimizer [23] with a fixed learning rate of 1×10^{-4} is applied to train PSVRF. The batch size is 32, and epochs are equal to 400. The experiments are implemented with 2$\times$ NVIDIA A100 40GB.

4.2. Evaluation of estimation accuracy

Evaluation: We evaluate the performance of the Estimator in PSVRF trained with T1 / T2 and that of the baseline [9] in A_1 Unseen, A_3 Seen, and A_3 Unseen with the Mean Absolute Error (MAE) between the predicted α and the ground truth, which is recorded in Table 2. In addition, we investigate the relationship between the estimation deviation i.e.,$\hat{\alpha}-\alpha$, of $\mathrm{PSVRF}_{\mathrm{T2}}$ and the disgusing parameters α applied in A_1 Unseen, which is shown in Fig. 3.

Results: From Table 2, we can find that although only the Phase Vocoder implemented by librosa is used to yield the training data, PSVRF can still precisely estimate the disguising parameters from different pitch scaling algorithms. In addition, a larger scale dataset can further boost the performance and generalization ability of PSVRF. It is noteworthy that PSVRF does not require any reference while it still achieves competitive results compared to the reference-based method. Fig. 3 reveals that the estimation of negative α is more accurate than that of the positive, which is consistent

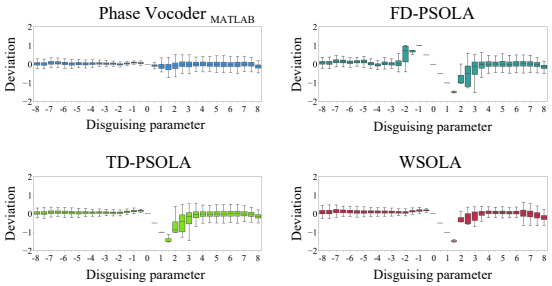


Fig. 3: Box-plot of the estimation deviation under various disguising parameters.

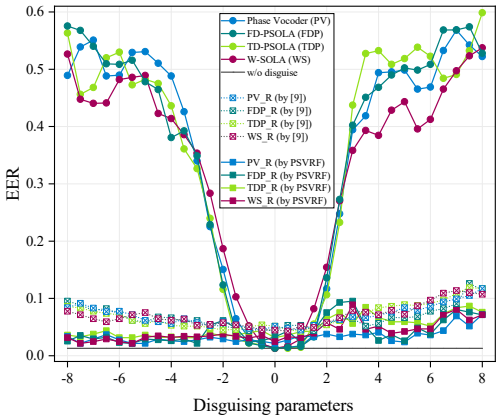


Fig. 4: ERR of the ASV model when faced with the pitch-shifted / restored samples from different subsets of A_1 Unseen.

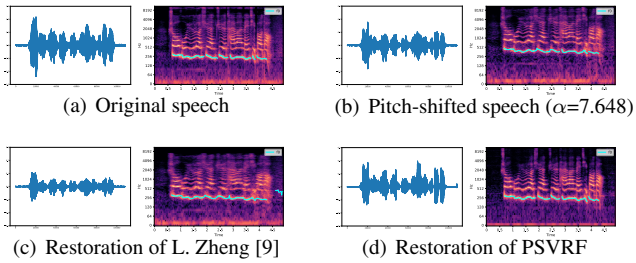


Fig. 5: Waveforms and spectrograms of an example utterance in A_1 Unseen.

with the conclusion in [6, 7] that pitch-lowered speech is easier to distinguish than pitch-raised speech. Besides, the tiny α is prone to be estimated as zero, resulting a linear deviation in the neighbourhood of zero. Although the estimation of disguising parameters through a single pitch-shifted speech can be solved by Estimator, it is actually an ill-posed problem. There are two explanations of how Estimator works: (1) the esitimator learns a mapping from the artifacts introduced by pitch-scaling algorithms to α; (2) Estimator learns a manifold which is composed of the original voice and its pitch-shifted counterpart, and mappings test samples to the learned manifold for generalization. The results in Table 2 reveal that Estimator can be generalized to various disguising algorithms. However, the artifacts introduced by different algorithms are usually different. In addition, more speakers' information can boost the performance of PSVRF. Therefore, we believe explanation (2) is more correct, which will be further studied in our future work.

4.3. Evaluation of restoration quality

Evaluation: We apply a typical ASV model termed ECAPA-TDNN [26] as an effective tool to evaluate the restoration quality of PSVRF and the baseline. Specifically, we qualitatively evaluate the improvement provided by different methods for the ASV model when faced with pitch-shifted samples from A_1 Unseen, which is shown in Fig. 4. In addition, we provide a visual comparison of the restoration obtained by different methods to further explain the advantage of PSVRF, which is shown in Fig. 5.

Results: Fig. 4 reveals that both the baseline and PSVRF can clearly enhance the performance of ASV when faced with pitch-shifted voice, while PSVRF provides higher restoration quality, which is reflected in the lower ERR of ASV. The main reason is that pitch-shifting algorithms will introduce artifacts during the disguising phase, and the baseline utilizes the pitch scaling algorithm to achieve the restoration, doubling the unpleasant artifacts and degrading the quality of restored speech. Differently, FRN in PSVRF is specifically designed to fit a mapping from fbank features of disguised speech to fbank features of original speech, which restores the pitch and removes the artifacts. This issue is further indicated in Fig. 5, where these two methods can both reconstruct the pitch of the original speech exactly, but PSVRF can reconstruct more clear formant and high-frequency information, resulting in a more realistic voice. However, the performance of PSVRF will obviously decline under tiny α, which is similar to or even worse than that of the baseline. The main reason is the estimation deviation of tiny α, which is mentioned in 4.2. In addition, the combination of FRN and Nerual Network can actually achieve high-quality pitch scaling besides the restoration, which will be further developed in our future work.

5. CONCLUSION

We propose a no-reference method termed *PSVRF* to estimate the disguising parameters of pitch scaling and restore pitch-shifted voice into original versions, which has great significance for the security of ASV. The experiments reveal that even compared with the SOTA reference-based baseline, PSVRF still obtains competitive results in both the estimation accuracy and the restoration quality. Furthermore, as a no-reference method, PSVRF can directly make existing ASV applications more resistant to pitch scaling without additional modifications. Future work would be investigating the improvement of PSVRF and its application besides anti-spoof.

6. REFERENCES

[1] A. Gomez-Alanis, J. A. Gonzalez-Lopez, S. P. Dubagunta, A. M. Peinado, and M. M. Doss, "On joint optimization of automatic speaker verification and anti-spoofing in the embedding space," *IEEE Trans. Inf. Forensics Security*, vol. 16, pp. 1579–1593, 2020.

[2] M. Aljasem, A. Irtaza, H. Malik, N. Saba, A. Javed, K. M. Malik, and M. Meharmohammadi, "Secure automatic speaker verification (sasv) system through sm-altp features and asymmetric bagging," *IEEE Trans. Inf. Forensics Security*, vol. 16, pp. 3524–3537, 2021.

[3] H. Tak, M. Todisco, X. Wang, J.-w. Jung, J. Yamagishi, and N. Evans, "Automatic speaker verification spoofing and deepfake detection using wav2vec 2.0 and data augmentation," *arXiv preprint arXiv:2202.12233*, 2022.

[4] J. Laroche, "Time and pitch scale modification of audio signals," in *Applications of digital signal processing to audio and acoustics*, pp. 279–309, Springer, 2002.

[5] H. Wu, Y. Wang, and J. Huang, "Blind detection of electronic disguised voice," in *2013 IEEE ICASSP*, pp. 3013–3017, 2013.

[6] H. Liang, X. Lin, Q. Zhang, and X. Kang, "Recognition of spoofed voice using convolutional neural networks," in *2017 IEEE GlobalSIP*, pp. 293–297, 2017.

[7] L. Wang, H. Liang, X. Lin, and X. Kang, "Revealing the processing history of pitch-shifted voice using cnns," in *2018 IEEE WIFS*, pp. 1–7, 2018.

[8] M. Pilia, S. Mandelli, P. Bestagini, and S. Tubaro, "Time scaling detection and estimation in audio recordings," in *2021 IEEE WIFS*, pp. 1–6, 2021.

[9] L. Zheng, J. Li, M. Sun, X. Zhang, and T. F. Zheng, "When automatic voice disguise meets automatic speaker verification," *IEEE Trans. Inf. Forensics Security*, vol. 16, pp. 824–837, 2021.

[10] Y. Gong, Y.-A. Chung, and J. Glass, "Ast: Audio spectrogram transformer," *arXiv preprint arXiv:2104.01778*, 2021.

[11] K. He, X. Chen, S. Xie, Y. Li, P. Dollár, and R. Girshick, "Masked autoencoders are scalable vision learners," in *Proc. CVPR*, pp. 16000–16009, 2022.

[12] Y. Gong, C.-I. Lai, Y.-A. Chung, and J. Glass, "Ssast: Self-supervised audio spectrogram transformer," in *Proc. AAAI*, vol. 36, pp. 10699–10709, 2022.

[13] A. Nagrani, J. S. Chung, and A. Zisserman, "Voxceleb: a large-scale speaker identification dataset," *arXiv preprint arXiv:1706.08612*, 2017.

[14] J. S. Chung, A. Nagrani, and A. Zisserman, "Voxceleb2: Deep speaker recognition," *arXiv preprint arXiv:1806.05622*, 2018.

[15] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks," *Communications of the ACM*, vol. 63, no. 11, pp. 139–144, 2020.

[16] A. v. d. Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, and K. Kavukcuoglu, "Wavenet: A generative model for raw audio," *arXiv preprint arXiv:1609.03499*, 2016.

[17] J. Kong, J. Kim, and J. Bae, "Hifi-gan: Generative adversarial networks for efficient and high fidelity speech synthesis," *Advances in Neural Information Processing Systems*, vol. 33, pp. 17022–17033, 2020.

[18] S. Liu, D. Su, and D. Yu, "Diffgan-tts: High-fidelity and efficient text-to-speech with denoising diffusion gans," *arXiv preprint arXiv:2201.11972*, 2022.

[19] Z. Kong, W. Ping, J. Huang, K. Zhao, and B. Catanzaro, "Diffwave: A versatile diffusion model for audio synthesis," *arXiv preprint arXiv:2009.09761*, 2020.

[20] H. Bu, J. Du, X. Na, B. Wu, and H. Zheng, "Aishell-1: An open-source mandarin speech corpus and a speech recognition baseline," in *2017 O-COCOSDA*, pp. 1–5, IEEE, 2017.

[21] Y. Shi, H. Bu, X. Xu, S. Zhang, and M. Li, "Aishell-3: A multi-speaker mandarin tts corpus and the baselines," *arXiv preprint arXiv:2010.11567*, 2020.

[22] B. McFee, C. Raffel, D. Liang, D. P. Ellis, M. McVicar, E. Battenberg, and O. Nieto, "librosa: Audio and music signal analysis in python," in *Proc. SciPy*, vol. 8, pp. 18–25, Citeseer, 2015.

[23] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[24] X. Zhu, G. T. Beauregard, and L. L. Wyse, "Real-time signal estimation from modified short-time fourier transform magnitude spectra," *IEEE Trans. Audio, Speech, and Language Processing*, vol. 15, no. 5, pp. 1645–1653, 2007.

[25] "Soundtouch audio processing library." [Online]. Available: `http://www.surina.net/soundtouch/`. Accessed: Jul. 2022.

[26] B. Desplanques, J. Thienpondt, and K. Demuynck, "Ecapa-tdnn: Emphasized channel attention, propagation and aggregation in tdnn based speaker verification," *arXiv preprint arXiv:2005.07143*, 2020.