Speech-to-Singing Conversion based on Boundary Equilibrium GAN

Da-Yi Wu\textsuperscript{1,2} and Yi-Hsuan Yang\textsuperscript{2}

\textsuperscript{1}Department of CSIE, National Taiwan University
\textsuperscript{2}Research Center for IT Innovation, Academia Sinica
r07922119@ntu.edu.tw, yang@citi.sinica.edu.tw

Abstract

This paper investigates the use of generative adversarial network (GAN)-based models for converting the spectrogram of a speech signal into that of a singing one, without reference to the phoneme sequence underlying the speech. This is achieved by viewing speech-to-singing conversion as a style transfer problem. Specifically, given a speech input, and optionally the F0 contour of the target singing, the proposed model generates as the output a singing signal with a progressive-growing encoder/decoder architecture and boundary equilibrium GAN loss functions. Our quantitative and qualitative analysis show that the proposed model generates singing voices with much higher naturalness than an existing non-adversarially-trained baseline. For reproducibility, the code will be publicly available at a GitHub repository upon paper publication.

Index Terms: Speech-to-singing conversion, singing voice synthesis, style transfer, adversarial training, encoder/decoder.

1. Introduction

The goal of singing voice synthesis is to create natural-sounding singing voices with some given conditions, such as the lyrics, pitch labels, or reference audio \cite{1,2,3,4,5}. The reference audio can be a singing passage of a person, and the task is to convert the timbre of the singing passage into the timbre of someone else \cite{6}. The reference audio can also be a passage of speech voice by someone, and the task is to convert it into a singing passage with the same timbre identity and underlying phoneme sequence, without reference to the underlying phoneme sequence \cite{7,8,9}. We are interested in speech-to-singing (STS) synthesis task in this paper, for its interesting applications in entertainment, karaoke, music production, and others.

Even through there are many properties shared by speech and singing signals, they cannot be easily converted to one another. Rhythm and phoneme representations in speech and singing are fairly different, and one singing sound can correspond to spoken passages with different speeds, tones, and even pronunciations \cite{6}. Moreover, melody information, less important for speech, is critical and indispensable for the expression of singing. Hence, in addition to preserving the linguistic content and timbre identity, an STS model would also need to generate singing that follows a pre-given or automatically-generated melody contour.

In the literature, there have been two main approaches to STS: model-based and template-based ones. For model-based STS, the work presented by Saitou \textit{et al.} \cite{7} is a representative one. They decompose the STS process into three main parts and process the signal using different control models. This involves lengthening the speech by a duration control model, generating the F0 contour with an F0 model, and modifying the timbre of the voice (so that it is singing-like) by a spectral model. Yet, the synthesis quality much depends on how accurate the phonemes are segmented and associated with the musical notes.

For template-based STS, proposed for the first time in \cite{10}, assumes that a high-quality-singing vocal, a.k.a., the “template singing,” is available as another audio reference. The inputs therefore comprise the speech and the template singing, which are to be firstly aligned with one another. The template singing is further used to extract the reference prosody which includes singing F0, aperiodicity index, singing formants, etc. This information is then used to estimate the parameters of singing synthesis from the aligned speech. As another example, Gao \textit{et al.} \cite{11} propose a deep learning based system for template-based STS conversion which conditions the network on the i-vector of a speaker while predicting the singing spectral parameters to preserve the speaker identity.

Different from previous works, we reinterpret STS as a \textit{style-transfer} problem, which can be viewed as the third approach to STS. Speech and singing are both very different styles, in that in singing we care more about the melody and rhythm. STS can therefore be treated as a style conversion. Among the style transfer architectures that have been proposed in the literature, we adopt the GAN \cite{12} architecture for its generalizability, and demonstrated effectiveness in some other musical style transfer tasks \cite{6,13}.

This work represents a continuation and extension of our prior work presented in \cite{9}, which is among the first attempts to approach STS with a deep-learning model that does not require any phoneme synchronization information or high-quality singing reference. In other words, only a speech passage and a target melody (F0) contour is needed for this model. We show in \cite{9} that even there is no other additional information, the model can surprisingly learn to sing, albeit the quality of synthesis is still not good enough. The limited quality of the generated singing can be attributed to many parts of the model, and it is our goal to improve upon this prior art here by introducing adversarial learning and modern style transfer techniques.

Specifically, our contributions are as follows. First, we modify the simple convolution architecture of \cite{7} into a progressive growing flow, which has been widely used to generate high quality audio in some recent works \cite{14,15,16}. Second, we extend the supervised learning framework into an unsupervised one. Specifically, an adversarial architecture based on boundary-equilibrium GAN \cite{12} is employed. Our new model is trained on both paired and unpaired data, while the prior model \cite{9} uses only a handful of paired data. Third, we use a MelGAN-based neural vocoder \cite{17} to replace the Griffin-Lim algorithm \cite{18} adopted in \cite{9} to further improve the sound quality.

Our experiments is conducted on both paired and unpaired data. For paired data, we use the the NUS sung and spoken lyrics corpus \cite{20} which is the largest public paired dataset. For unpaired data, we use the DAMP corpus \cite{21} which \ldots
We perform spectra-to-spectra conversion in an encoder-decoder framework, as depicted in Fig. 1. The input speech is transformed into a log mel-spectrogram, and the F0 contour is extracted by a vocal melody extractor from a different source such as humming or reference singing. Time-stretch the mel-spectrogram of speech to the same length as its target F0 contour, and apply two encoders to encode speech and pitch information separately. Then, the decoder takes the concatenation of these two encodings and generates the singing output, with skip-connections from two encoders to encode speech and pitch information separately. Figure 1: Diagram of the proposed model architecture, which is extended from the model we previously presented in [9]. The input speech is represented by a log mel-spectrogram, and the target melody contour is represented into one-hot format. Our encoder-decoder architecture learns the STS conversion by supervised and unsupervised learning jointly. We use different colors to highlight the parts that we have improved over the prior art [9].

Details of the proposed encoder and decoder. GN represent group normalization, Encoder consists of convolution banks, and decoder upsamples the time-frequency representation by interpolation and concatenation.

2. Methods

Given an input time-domain speech signal and a target F0 contour, the pre-processing consists of the following steps:

- **Log-magnitude representation:** We compute the magnitude of mel-spectrogram for the speech signal and apply element-wise logarithm transformation, yielding a matrix $X \in \mathbb{R}^{F \times T}$, with $F$ frequency bins and $T$ time frames.

- **Random resampling (RR):** It is reasonable that one singing or musical score can match various speed of speech voice. Hence, we random resample the input speech as proposed in [23], which changes the rhythm of the input speech. This involves two steps. We firstly divide the mel-spectrogram of speech into segments of random lengths. Then, we randomly stretch or squeeze each segment along the time dimension. In our case, we divide the speech into segments of random length drawn from 16–32 frames, and each segment is interpolated linearly by a factor from 0.5 to 2.

- **Time stretching (TS):** Speech mel-spectrogram and F0 contour can be of widely differing lengths. However, existing models addressing the variable-length task, such as the sequence-to-sequence model Tacotron [24], often perform on discrete-to-discrete, or discrete-to-continuous tasks. Spectra-to-spectra learning tasks like STS are concerned with a continuous-to-continuous transformation that has not been widely studied. Hence, we use a simpler fixed-length setting. The input mel-spectrogram is interpolated linearly to the same length as the F0 contour.

- **Vocal pitch contour.** Melody contours are extracted from a singing audio using the CREPE model [22], a state-of-the-art monophonic pitch tracker that is open source. Moreover, we convert the continuous-valued extracted F0 to integer-valued MIDI note by referencing to the hz-to-midi function in the librosa package [25], and convert it into one-hot format. We set up to 128 different MIDI notes. As a result, the melody contour $C$ is represented as a sequence of one-hot vector indicating the target MIDI note per frame. It has the same length of the mel-spectrogram, namely $C \in \mathbb{N}^{128 \times T}$. Following the prior work [9], in the case of training with paired data, we extract the melody contour from the singing counterpart of the input speech.

2.2. Encoder and Decoder

As shown in Fig. 2, the input speech adopts a fully 1D-convolutional architecture, and both time and frequency are downsampled by a factor of 8 to obtain the latent code. Instance normalization [28] is employed before 1D-convolution layer as a “style remover,” and we use $3 \times 1$ convolution kernels with striding 2 instead of max-pooling followed by LeakyReLu. Pitch encoder apply embedding layer to convert melody contour into embedding first, and then pass it through the fully 1D-convolution architecture.

As for the decoder, we use a progressive-growing architecture, which has been recently shown to be effective as a “spectrogram generator” [15, 27]. It consists of two 1D $3 \times 1$ kernel convolutions with stride 1, Group-Norm layer [26], and two up sampling modules. Following [16], nearest neighbor interpolation is applied instead of 1D convolution-transposed. And, Upsampling in frequency domain is performed by concatenation instead of a convolution layer, in the similar light of [15, 16].

Audio examples of the generated conversions can be found here: https://ericwudayi.github.io/Speech2Singing-DEMO/
2.3. BEGAN

BEGAN is an energy-based GAN architecture [17]. While the original GAN [29] matches the distributions between the real and generated samples directly, an energy-based GAN matches the distribution of loss using an auto-encoder architecture. Moreover, BEGAN relaxes the equilibrium of the auto-encoder loss using a hyper-parameter \( \gamma \in [0, 1] \) (a.k.a. diversity ratio), defined as

\[
\gamma = \mathbb{E}[L(Y)]/\mathbb{E}[L(y)],
\]

where \( G(x) \) is a generated sample, \( y \) is a real sample, and \( L(\cdot) \) is the reconstruction loss function of the auto-encoder. The \( \gamma \) term balances the diversity and quality. Lower values of \( \gamma \) make the discriminator focuses more on real samples, generating samples with better quality but less diversity. In contrast, higher values of \( \gamma \) improve the diversity but lower the quality.

We use BEGAN as our unpaired data trainer for its stable training process observed in our pilot study. It has also been shown in [30] and [27] that BEGAN performs better than some other commonly-used GAN models for generating audio.

2.4. Training

Our model is trained with by minimizing the BEGAN loss and L1 loss jointly. Formally, given an input log mel-spectrogram \( X \), a melody contour \( C \), and a target singing log mel-spectrogram \( Y \), the losses of the generator and discriminator are defined as:

\[
\begin{align*}
L_D &= L(Y) - k_t L(G(X, C)), \\
L_G &= L(G(X, C)) + \beta |Y - G(X, C)|_1,
\end{align*}
\]

where \( L_D \) only depends on BEGAN loss, and the variable \( k_t \in [0, 1] \) controls how much emphasis is put on \( L(G(x)) \). The update of \( k_t \) is controlled by the diversity ratio \( \gamma \) according to

\[
k_{t+1} = k_t + \lambda (\gamma L(Y) - L(G(X, C))).
\]

In Eqn. 2, we also use the pixel-wise L1 spectrogram loss to \( L_G \) to achieve supervised learning in paired data, scaling with a \( \beta \) factor to avoid overfitting. As for the case of training with unpaired data, the generator is trained with \( L(G(x)) \) only.

2.5. Vocoder

Neural vocoders such as the WaveNet vocoder [31] have been shown to outperform the traditional Griffin-Lim algorithm [19] for converting time-frequency representations to waveforms. Among the neural vocoders that have been proposed, we adopt MelGAN [18] for its remarkable efficiency and generalizability.

Out of the 20 unique songs in the dataset, we keep one song (with two recordings) as our test set. The test singer is only present in one recording in our training set, and the test song is not seen at all in the training data.

Due to the small size of the NUS dataset, we originally plan to perform data augmentation using unpaired data with both speech-only and singing-only datasets. For speech, we consider adding the LJSpeech dataset [32], which is a single speaker dataset with 24 hours of reading audio. For singing, we consider using the DAMP dataset [21], which is a multi-singer dataset comprised of about 6,000 songs.

The use of LJSpeech for augmenting the speech data, however, turns out to be difficult. This is because, in our STS setting, we need to find a way to create the target melody contour for each input speech from LJSpeech. The melody contour should correlate well to the number of words from the spoken lines. And, it is not natural to convert the speech with arbitrary melody contour. We attempt to give the pitch contour \( C \) by randomly sampling a pitch contour from our singing dataset, but the result shows that it actually hurts the audio quality. Therefore, for simplicity, we decide to augment only the singing data with DAMP, and drop the LJSpeech part.

To extract the more representative training data, we exclude the segments of song that contains silences of longer than one second. Moreover, we remove the silence from speech by using the phoneme-duration annotation. All the combinations are constrained to have three or more words.

Implementation details. All the neural network implementations and audio processing procedures are performed using pytorch and librosa [25]. The time domain signals are resampled from 44k to 22k Hz. We compute STFT with 1,024-pt FFT size, 12.5 milliseconds hop size, and transform it into 80-bin mel-scale. We set BEGAN parameters \( \lambda = 0.01 \) and initialize \( k_0 = 0, \gamma = 0 \). We set supervised learning factor \( \beta = 0.5 \) and use Adam as our optimizer with initial learning rate 0.001 and exponential decrease factor of 0.99. We train the networks for 20k steps with 32 batch size. The training process takes about 5 hours to complete, using an NVIDIA RTX 1080-Ti GPU.

Our multi-singer MelGAN vocoder is trained on the union of the NUS dataset [20] and two other sources of unaccompanied singing data, the DSD [33] and MUSDB18 datasets [34]. The whole training process take 1000k steps, and about 2 weeks.

Phoneme synchronization (PhSync). To quantify how much the burden of modelling phoneme duration affects the system, we follow the settings in [9] and stretch/shrink each phone in the input speech to be the same length as it is in the target singing. The duration for each phoneme is obtained from the phone-level annotations for speech and singing.

3.2. System evaluated

We create several variants of our system to extensively evaluate the effect of each of the modifications we propose.

- **Baseline**: Uses the model architecture proposed in the prior art [9], which is trained through multi-task learning with phoneme prediction, using only the paired data. It uses log spectrograms as its input, not mel-spectrograms.
- **Decoder (D):** Uses the modified version of the decoder, and trained with the MSE loss. We use the spectrograms here as the input for fair comparison with the Baseline.
- **Decoder + Adversarial (D + A):** Uses the modified version of the decoder, and trained with adversarial and MSE losses jointly. Also use the spectrogram features.
The participants were then asked to specify their preference among the two systems in terms of naturalness. For all pairs of the systems (i.e., ‘Baseline v.s D,’ ‘D v.s. D+V,’ ‘D+V v.s. D+V+A’), each participant was first asked to listen to the input speech and compare the outputs of a selected pair of the systems. The participants were then asked to specify their preference among the two systems in terms of naturalness. For all pairs of the systems, the percentage of votes are reported for each option. We highlight the best result obtained by the system in each group.

- **Decoder + Neural Vocoder (D+V):** Uses our modified version of the decoder, and trained on the log mel-spectrogram features. The output is converted to waveform by MelGAN [18] instead of Griffin-Lim.

- **Proposed model (D + V + A):** The proposed network trained with adversarial loss and MSE loss jointly using both paired and unpaired data, and the output is also converted into waveform by MelGAN.

- **Proposed Model + PhSync:** Denotes our proposed system trained in frame synchronization setting.

**Objective evaluation.** Following [9], we use log-spectral distance (LSD) and F0 raw chroma accuracy (RCA) as the objective metrics. LSD evaluates the dissimilarity between two spectra, while RCA evaluates melody correctness. LSD is computed by averaging the Euclidean distance between true and predicted log spectrogram or log mel-spectrogram frames over time, for frequencies between 100 Hz to 3.5 kHz. RCA is computed according to [35] between a target waveform and the model output, and we set the maximum tolerance deviation between target and output as 50 cents in frequency value. The systems are evaluated by selecting random 50 test samples with speech duration of at least 2 seconds and then averaging the scores over all the samples.

**Subjective evaluation:** We are mainly interested in three parts. Is our decoder architecture better than the prior one employed in [9]? Does the neural vocoder with 80 bins melspectrogram performs better than the Griffin-Lim algorithm with 512 bins spectrogram? Does adversarial learning help the model generate more natural-sounding singing?

Hence, instead of doing objective evaluations on all the systems, we conducted preference listening test on a selective pairs of the systems (i.e., ‘Baseline v.s. D,’ ‘D v.s. D+V,’ ‘D+V v.s. D+V+A’). Each participant was first asked to listen to the input speech and compare the outputs of a selected pair of the systems. The participants were then asked to specify their preference among the two systems in terms of naturalness. For all pairs of systems, the percentage of votes are reported for each option.

### 3.3. Results and Discussion

**Objective evaluation:** The result is shown in Table 1. Several observations can be made. First, Decoder performs noticeably better than Baseline on both LSD and RCA. This indicates that our decoder architecture combined with the progressive-growing architecture works better for STS. Second, we find that ‘Decoder + Adversarial’ also performs better than ‘Decoder-only’ on both 512-bin spectrogram and 80-bin mel-spectrogram representations, suggesting that unsupervised learning with the BEGAN architecture improves the results.

**Subjective evaluation:** The response from 38 participants recruited from the Internet for our listening test is summarized in Fig. 3. Each of our modifications seems to outperform the corresponding ablated version. Key takeaways are: We can do better STS by using a neural vocoder on mel-spectrograms; and the use of adversarial learning and unpaired data is beneficial.

#### 3.4. Other Experiments and Future works
Melody information may not be easy to obtain most of the times, and a perfect STS system should learn how to sing given only speech audio. Hence, we attempt to directly transform speech to singing with no melody information. The cycle-BEGAN architecture is employed to achieve unsupervised learning, and models are trained with adversarial loss and cycle reconstruction loss jointly. However, results show that it can not generate natural singing. Model does not learn to generate coherent melody across time, and the reason may be that it is too hard for the generator to learn a global information like melody coherence with a GAN architecture. We plan to study in our future work a two-step model that generates the melody contour from speech first, and then generates the singing. Another idea is to use an auto-regressive models such as the VQVAE [36, 37] so that the output sequence is conditioned on previous states.

### 4. Conclusions

In this paper, we have presented variant settings to improve an end-to-end speech-to-singing conversion neural net that takes only speech and target melody contour as the input. We modify different aspects of the network, mainly with GAN-based methods. Moreover, we validate the effectiveness of our model via both objective and subjective studies, seeing promising improvements. We are interested in using sequence-to-sequence models for this task, and in creating a model that does not require the target melody contour to be specified.

---

We remind that the first three methods take the magnitude spectrograms as inputs, while the other methods deal with the mel-spectrograms. Therefore, the values of ‘LSD’ and ‘LSD (mel)’ are not comparable.

| System                      | LSD ↓ | LSD (mel) ↓ | RCA ↑ |
|-----------------------------|-------|-------------|-------|
| Baseline [9]                | 9.97  | —           | 0.760 |
| Decoder                     | 9.36  | —           | 0.801 |
| Decoder + Adversarial       | 9.21  | —           | 0.820 |
| Decoder + Vocoder           | —     | 1.15        | 0.811 |
| Proposed                    | —     | 1.13        | 0.832 |
| Proposed + PhSync           | —     | 1.07        | 0.816 |

Table 1: Results on objective metrics for different proposed STS systems. Log-spectral distance (LSD; in db) is the lower the better, while raw chroma accuracy (RCA) the inverse. The first three rows present the results of spectrogram input system with various settings. The second and third last row presents the result of a neural vocoder system, operating on mel-spectrograms. The last row uses phone-annotation information. Therefore, ‘LSD’ and ‘LSD (mel)’ are calculated over magnitude spectrograms and mel spectrograms, respectively. We highlight the best result obtained by the system in each group.

![Figure 3: Subjective evaluation results for pairs of systems.](image-url)
5. References

[1] K. Saino, H. Zen, Y. Nankaku, A. Lee, and K. Tokuda, “An HMM-based singing voice synthesis system,” in Proc. International Conference on Spoken Language Processing, 2006.

[2] R. Valle, J. Li, R. Prenger, and B. Catanzaro, “Mellotron: Multispeaker expressive voice synthesis by conditioning on rhythm, pitch and global style tokens,” arXiv preprint arXiv:1910.11997, 2019.

[3] K. Nakamura, K. Hashimoto, K. Oura, and K. T. Yoshikiko Nankaku, “Singing voice synthesis based on convolutional neural networks,” arXiv preprint arXiv:1904.06668, 2019.

[4] J. Lee, H.-S. Choi, C.-B. Jeon, J. Koo, and K. Lee, “Adversarially trained end-to-end Korean singing voice synthesis system,” in Proc. INTERSPEECH, 2019.

[5] Y. Gu, X. Yin, Y. Rao, Y. Wan, B. Tang, Y. Zhang, J. Chen, Y. Wang, and Z. Ma, “ByteSinging: A Chinese singing voice synthesis system using duration allocated encoder-decoder acoustic models and wavernet vocoders,” arXiv preprint arXiv:2004.11012, 2020.

[6] C.-W. Wu, J.-Y. Liu, Y.-H. Yang, and J.-S. R. Jang, “Singing style transfer using cycle-consistent adversary equilibrium generative adversarial networks,” in Proc. Joint Workshop on Machine Learning for Music, 2018.

[7] T. Saitou, M. Goto, M. Unoki, and M. Akagi, “Speech-to-singing synthesis: Converting speaking voices to singing voices by controlling acoustic features unique to singing voices,” in Proc. IEEE Workshop on Applications of Signal Processing to Audio and Acoustics, 2007, pp. 215–218.

[8] K. Vijayan, H. Li, and T. Toda, “Speech-to-singing voice conversion: The challenges and strategies for improving vocal conversion processes,” IEEE Signal Processing Magazine, vol. 36, no. 1, pp. 95–102, 2019.

[9] J. Parekh, P. Rao, and Y.-H. Yang, “Speech-to-singing conversion in an encoder-decoder framework,” arXiv preprint arXiv:2002.06595, 2020.

[10] L. Cen, M. Dong, and P. Chan, “Template-based personalized singing voice synthesis,” in IEEE International Conference on Acoustics, Speech and Signal Processing, 2012, pp. 4509–4512.

[11] X. Gao, X. Tian, R. K. Das, Y. Zhou, and H. Li, “Speaker-independent spectral mapping for speech-to-singing conversion,” in Proc. APSIPA ASC, 2019.

[12] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, “Unpaired image-to-image translation using cycle-consistent adversarial networks,” in Proc. IEEE International Conference on Computer Vision, 2017.

[13] N. Mor, L. Wolf, A. Polyak, and Y. Taigman, “A universal music translation network,” arXiv preprint arXiv:1805.07848, 2018.

[14] T. Karras, T. Aila, S. Laine, and J. Lehtinen, “Progressive growing of GANs for improved quality, stability, and variation,” arXiv preprint arXiv:1710.10196, 2017.

[15] S. Vasquez and M. Lewis, “Melnet: A generative model for audio in the frequency domain,” arXiv preprint arXiv:1906.01083, 2019.

[16] J.-Y. Liu, Y.-H. Chen, Y.-C. Yeh, and Y.-H. Yang, “Unconditional audio generation with generative adversarial networks and cycle regularization,” submitted to INTERSPEECH, 2020.

[17] D. Berthelot, T. Schumm, and L. Metz, “BEGAN: Boundary equilibrium generative adversarial networks,” arXiv preprint arXiv:1703.10717, 2017.

[18] K. Kumar, R. Kumar, T. de Boissiere, L. Gestin, W. Zhen, T. J. Sotelo, A. de Brébisson, Y. Bengio, and A. C. Courville, “MelGAN: Generative adversarial networks for conditional waveform synthesis,” Proc. NeurIPS, pp. 14910–14921, 2019.

[19] D. Griffin and J. Lim, “Signal estimation from modified short-time fourier transform,” IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 32, no. 2, pp. 236–243, 1984.

[20] Z. Duan, H. Fang, B. Li, K. C. Sim, and Y. Wang, “The NUS sung and spoken lyrics corpus: A quantitative comparison of singing and speech,” in Proc. Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, 2013, pp. 1–9.

[21] J. C. Smith, “Correlation analyses of encoded music performance,” Ph.D. Thesis, Stanford University, 2013.

[22] J. W. Kim, J. Salamon, P. Li, and J. P. Bello, “CREPE: A convolutional representation for pitch estimation,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing, 2018, pp. 161–165.

[23] K. Qian, Y. Zhang, S. Chang, X. Yang, and M. Hasegawa-Johnson, “AutoVC: Zero-shot voice style transfer with only autoencoder loss,” arXiv preprint arXiv:1905.05879, 2019.

[24] J. Shen et al., “Natural TTS synthesis by conditioning wavenet on mel spectrogram predictions,” in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing, 2017, pp. 4779–4783.

[25] B. McFee, C. Raffel, D. Liang, D. P. W. Ellis, M. McVicar, E. Battenberg, and O. Nieto, “librosa: Audio and music signal analysis in Python,” in Proc. Python in Science Conf., 2015, pp. 18–25, [Online] [https://librosa.github.io/librosa]

[26] D. Ulyanov, A. Vedaldi, and V. S. Lempitsky, “Instance normalization: The missing ingredient for fast stylization,” arXiv preprint arXiv:1607.08022, 2016.

[27] J.-Y. Liu, Y.-H. Chen, Y.-C. Yeh, and Y.-H. Yang, “Score and lyrics-free singing voice generation,” in Proc. International Conference on Computational Creativity, 2020.

[28] Y. Wu and K. He, “Group normalization,” in Proc. European Conference on Computer Vision, 2018, pp. 3–19.

[29] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” in Proc. Advances in Neural Information Processing Systems, 2014, pp. 2672–2680.

[30] C. Wu, J. Liu, Y. Yang, and J. R. Jang, “Singing style transfer using cycle-consistent boundary equilibrium generative adversarial networks,” in Proc. Joint Workshop on Machine Learning for Music, extended abstract, 2018.

[31] 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.

[32] K. Ito, “The LJ speech dataset,” 2017. [Online]. Available: [https://keithito.com/LJ-Speech-Dataset/]

[33] A. Liutkus et al., “The 2016 signal separation evaluation campaign,” in Proc. International Conference on Latent Variable Analysis and Signal Separation, Cham, 2017, pp. 323–332.

[34] Z. Rafii, A. Liutkus, F.-R. Stöter, S. I. Milimakis, and R. Bittner, “The MUSDB18 corpus for music separation,” 2017. [Online]. Available: [https://doi.org/10.5281/zenodo.1117372]

[35] C. Raffel, B. McFee, E. Humphrey, J. Salamon, O. Nieto, D. Liang, D. P. Ellis, and C. Raffel, “mir_eval: A transparent implementation of common MIR metrics,” in Proc. International Society for Music Information Retrieval Conference, 2014.

[36] A. van den Oord, O. Vinyals, and K. Kavukcuoglu, “Neural discrete representation learning,” arXiv preprint arXiv:1711.00937, 2017.

[37] P. Dhariwal, H. Jun, C. Payne, J. W. Kim, A. Radford, and J. Sutskever, “Jukebox: A generative model for music,” arXiv preprint arXiv:2005.00341, 2020.