Mandarin Singing Voice Synthesis with Denoising Diffusion Probabilistic Wasserstein GAN

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Abstract—Singing voice synthesis (SVS) is the computer production of a human-like singing voice from given musical scores. To accomplish end-to-end SVS effectively and efficiently, this work adopts the acoustic model-neural vocoder architecture established for high-quality speech and singing voice synthesis. Specifically, this work aims to pursue a higher level of expressiveness in synthesized voices by combining the diffusion denoising probabilistic model (DDPM) and Wasserstein generative adversarial network (WGAN) to construct the backbone of the acoustic model. On top of the proposed acoustic model, a HiFi-GAN neural vocoder is adopted with integrated fine-tuning to ensure optimal synthesis quality for the resulting end-to-end SVS system. This end-to-end system was evaluated with the multi-singer Mpop600 Mandarin singing voice dataset. In the experiments, the proposed system exhibits improvements over previous landmark counterparts in terms of musical expressiveness and high-frequency acoustic details. Moreover, the adversarial acoustic model converged stably without the need to enforce reconstruction objectives, indicating the convergence stability of the proposed DDPM and WGAN combined architecture over alternative GAN-based SVS systems.1

I. INTRODUCTION

Singing voice synthesis (SVS) aims to generate singing voices as natural and expressive as those of human singers. The attention from both academia and commercial corporations has pushed the boundaries of SVS with neural networks in recent years.

Although there are neural network-driven SVS systems designed to generate waveforms directly from the musical scores [1], [2], the most prominent system design is to split the generation pipeline into two stages. First, an acoustic model frontend consumes the musical score to estimate the intermediate acoustic features for the singing voice; then, a backend synthesizes the final audio waveform from those acoustic features. While the intermediate acoustic features can be spectrograms [3] or the WORLD vocoder [4] parameters [5], [6], Mel-spectrograms are preferred by most neural SVS systems pursuing the highest audio quality as in [7]–[9]. These Mel-spectrogram intermediates are transformed to audio waveforms with neural vocoder backends such as Parallel WaveGAN [10], HiFi-GAN [11], or the novel singing-specific SawSing [12] neural vocoder.

In this setup, the acoustic model determines how musically natural and expressive the synthesized singing voice will be. Numerous deep learning techniques have been deployed as backbone modules for constructing acoustic models. Some of the noticeable techniques in the landmark systems in-clude long-short term memory machine (LSTM) [13], [14], WaveNet [1], [6], and Transformer [5], [7]. These systems commonly employ reconstructive L1 or L2 loss to train the acoustic model to estimate the acoustic features. Nevertheless, generative models trained on simple reconstructive targets often suffer from over-smoothing and producing estimations that approach the mean/median of the target distribution but lack human-like variations.

Therefore, some of the recent advancements in SVS acoustic models are based on generative adversarial networks (GANs) and denoising diffusion probabilistic models (DDPMs). Regarding musical naturalness and expressiveness, GANs have proven to be an enhancement in multiple SVS systems [3], [8], [15], but they are usually less stable in training and may require dataset-specific hyperparameters. On the other hand, DDPM is a generative model that yield promising performance across domains, such as image generation [16], [17], neural vocoding [18], speech enhancement [19], and speech or singing voice synthesis [9], [20]. Considering their high performance, the confluence of the two techniques was a natural development. The combination of GAN and DDPM has shown excellent performances in image generation [21] with a subsequent attempt in speech synthesis [22].

To explore such a combined architecture of DDPM and GAN, this work trains the DDPM acoustic model adversarially with a Wasserstein GAN (WGAN) algorithm. Among different kinds of GANs, WGAN is the one that promises to approximate the real data distribution even when this probability density may not be approachable by other GAN metrics [23], [24]. This property makes it an ideal GAN algorithm for SVS where the complicated singing voice distribution is usually supported by a relatively small dataset, owing to data collection difficulties. Additionally, this work

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1Evaluation audio samples can be found at: https://yinping-cho.github.io/ diffwgan/svs.github.io/

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proposes a Musical-Score-Conditioned (MSC)-discriminator that incorporates information of the sung contents to further prevent mode collapses that are often encountered in GAN-based synthesis models.

II. NOising DIFFUSION WASsERSTEIN GAN

The following section introduces DDPM with Wasserstein GAN (WGAN) [23]. Section II-A states the denoising diffusion probabilistic model formulation, Section II-B explores why and how a Wasserstein GAN is applied to DDPM, and Section II-C presents the denoising diffusion WGAN formulated for SVS in this work.

A. Diffusion Denoising Probabilistic Model

The working of DDPM is characterized by a Gaussian Markov chain with a noising process and a denoising process, which are visualized in Fig. 1.

![Diagram of Denoising Diffusion Process](image)

**Fig. 1:** Visualization of the noising diffusion process and the denoising diffusion process with a Mel-spectrogram.

The noising process transforms a true data sample \( x_0 \), in this case a clean Mel-spectrogram, to a unit normal noise \( x_{T} \sim \mathcal{N}(0, I) \) of the same dimensions, formulated as:

\[
q(x_1 | x_{t-1}) = \prod_{t=1}^{1} q(x_t | x_{t-1}), t = 1, 2, 3, ..., T; \tag{1}
\]

where the variance schedule \( \{\beta_t\} \) is pre-defined according to an exponential scheme same as in [21]. Conversely, \( q(x_0) \) denotes the data generation of a true Mel-spectrogram, and \( q(x_{t-1} | x_t) \) is thus the true denoising diffusion transition.

The denoising process gradually synthesizes an estimated Mel-spectrogram \( \tilde{x}_0 \) from a random initial noise \( x_T \) with model parameter \( \theta \) in the form of a denoising process:

\[
p_\theta(\tilde{x}_0 | T) = p(x_T) \prod_{t=1}^{T} p_\theta(\tilde{x}_t | x_t), t = T, T-1, \ldots, T; \tag{2}
\]

where the denoising transition is estimated by the acoustic model generation \( f_\theta(x_t, t) \) is estimated by the acoustic model generation \( f_\theta(x_t, t) = G_\theta(x_t, t, \text{ms}, \text{id}) \), with \( \text{ms} \) denoting the musical score with lyrics, \( \text{id} \) being the singer identity, and \( G_\theta(\cdot) \) as the neural network generator with learnable parameter \( \theta \).

Since the diffusion sampling is simply a Gaussian sampling, \( \tilde{x}_t \) can be computed in one step as:

\[
\tilde{x}_t = \sqrt{\alpha_t} x_t + \sqrt{1 - \alpha_t} \epsilon, \epsilon \sim \mathcal{N}(0, I) \tag{4}
\]

and \( q(\tilde{x}_{t-1} | x_t, \tilde{x}_0) \) is efficiently obtained with

\[
q(x_{t-1} | x_t, x_0) = \mathcal{N}(x_{t-1}; \tilde{\mu}(x_0, x_t, \beta_t I)), \tag{5}
\]

where the denoising distribution \( \tilde{x}_{t-1} | x_t, \tilde{x}_0 \) is pre-computed once the variance schedule \( \{\beta_t\} \) is defined as a hyperparameter of the process [16], [21].

B. Diffusion Wasserstein GAN

To achieve good synthesis quality with the denoising process introduced in Subsection II-A, DDPMs usually set the number of time steps \( T \) to a large number (hundreds to thousands) and keep \( \beta_t \) very small. This way, both the noising \( q(x_t | x_{t-1}) \) and the denoising \( q(x_{t-1} | x_t) \) diffusion transitions of the true data are sufficiently Gaussian, making it easy for the model to approximate the true denoising transition:

\[
p_\theta(\tilde{x}_{t-1} | x_t) \approx q(x_{t-1} | x_t). \tag{6}
\]

However, setting a large \( T \) and small \( \{\beta_t\} \) makes the synthesis process much more time-consuming both in the training and the inference phases. Consequently, we adopt a more efficient Variance Preserving (VP) SDE scheme proposed in [25], computing \( \{\beta_t\} \) according to

\[
\beta_t = 1 - \exp\{\beta_{\text{min}} (\frac{1}{T} - 0.5(\beta_{\text{max}} - \beta_{\text{min}}) \frac{2t - 1}{T^2})\}, \tag{6}
\]

where we set \( \beta_{\text{max}} = 20 \), \( \beta_{\text{min}} = 0.1 \), and the number of time steps \( T = 4 \), found as the best-performing hyperparameters in [21].

Nevertheless, this few-step, big-jump diffusion scheme poses a much greater challenge to the acoustic model. Since the distribution of Mel-spectrograms is not Gaussian and is empirically sparse, the diffusion transition \( q(x_{t-1} | x_t) \) is a complicated conditional distribution that is hard to estimate.

Thus, the objective for the denoising generator is formulated as:

\[
\min_\theta \sum_{t \geq 1} \mathbb{E}_{q(x_t)} [D_{\text{adv}}(q(x_{t-1} | x_t) || p_\theta(\tilde{x}_{t-1} | x_t))], \tag{7}
\]

which aims to match the true transition \( q(x_{t-1} | x_t) \) and the model’s synthesis transition \( p_\theta(\tilde{x}_{t-1} | x_t) \) by minimizing an adversarial objective \( D_{\text{adv}} \) that estimates the Wasserstein Distance with adversarial neural networks.

C. Diff-WGAN formulated for SVS

The adversarial objective demands the conditional discriminator to distinguish the true prior Mel-spectrogram \( x_{t-1} \) and the estimated \( \tilde{x}_{t-1} \) generated by the acoustic model according to the definition in Equation 3.
For the SVS task, we formulated the generator and discriminator as:

\[
\text{Generator: } G_\theta(x_t, t, \text{ms}, \text{id})
\]

\[
\text{Discriminator: } D_\phi(x_{t-1}, x_t, t, s_{\text{pho}}, s_{\text{len}}, s_{\text{pit}}, \text{id})
\]

where \( \theta \) and \( \phi \) denote the learnable parameters for the two networks, \( \text{ms} \) denotes the musical score encoded by the musical score encoder and variance adaptor modules, \( \text{id} \) denotes singer identity, and \( s_{\text{pho}}, s_{\text{len}}, s_{\text{pit}} \in \mathbb{R}^{1 \times L_p} \) denote the musical score’s phone sequence, note-length sequence, and note-pitch sequence.

In addition to the real/fake \( x_{t-1}/\tilde{x}_{t-1} \), the discriminator is provided with a real prior \( x_t \) and the corresponding time step \( t \) as completion of conditions for a noising diffusion transition. In addition, the musical score’s information and the singer id \( \text{id} \) are encoded and fed as auxiliary information since they were found to improve training stability and enhance linguistic features in related studies [22], [26].

To enforce the Lipschitz continuity required by WGAN [23], we applied the gradient penalty [27]. Hence we have the minimization criterion for the discriminator as

\[
L_D = L_{WD} + \lambda_{GP} L_{GP},
\]

where the Wasserstein distance criterion is

\[
L_{WD} = \sum_{t \geq 1} -E_{q(x_t)q(x_{t-1}|x_t)}[D_\phi(x_{t-1}, x_t, t, s_{\text{pho}}, s_{\text{len}}, s_{\text{pit}}, \text{id})] + E_{q(x_{t-1})p_\theta(\tilde{x}_{t-1}|x_t)}[D_\phi(\tilde{x}_{t-1}, x_t, t, s_{\text{pho}}, s_{\text{len}}, s_{\text{pit}}, \text{id})],
\]

with \( \lambda_{GP} = 10.0 \) for the gradient penalty:

\[
L_{GP} = \sum_{t \geq 1} E_{x_{t-1} \sim P(\tilde{x}_{t-1})} ||\nabla_{x_{t-1}} D_\phi(x_{t-1}, x_t, t, s_{\text{pho}}, s_{\text{len}}, s_{\text{pit}}, \text{id})||_2 - 1 ||^2,
\]

where \( \tilde{x}_{t-1} = \alpha x_{t-1} + (1 - \alpha) \tilde{x}_{t-1}, \alpha \sim U(0, 1). \)

As defined by [23], the generator’s adversarial loss is formulated against that of the discriminator as

\[
L_{adv} = \sum_{t \geq 1} E_{q(x_t)}[D_\phi(G_\theta(x_t, t, \text{ms}, \text{id}), x_t, t, s_{\text{pho}}, s_{\text{len}}, s_{\text{pit}}, \text{id})].
\]

III. PROPOSED SYSTEM

As depicted in Fig. 2a, our proposed SVS system is composed of an acoustic model that synthesizes Mel-spectrograms from musical score inputs and a HiFi-GAN neural vocoder [11] that synthesizes waveforms from estimated Mel-spectrograms. The specifications of the acoustic model are presented in Table I.

A. Acoustic Model

1) Transformer Encoder: The encoder is based on FastSpeech2 [28] and DiffSinger’s encoder modules [9]. Here, we exploit Mandarin phonology to pair a note on the score with a syllable in the lyrics and decompose every syllable into an initial-final pair, the details of which can be found in our previous work [14]. Each initial and each final are treated as
a phone in the context of this work. The phone sequence and the note-length sequence are embedded, added together and passed through the Transformer stack to become the phone latent sequence.

2) Variance Adaptor: The Variance Adaptor contains a duration predictor and a sequence-length regulator which expands the length of the phone latent sequence from token-level to frame-level, matching that of the ground truth Mel-spectrograms, as in [5], [9], [28]. In the meantime, the note-pitch information \(s_{\text{pit}}\) is separately expanded by the sequence-length regulator, and added to the phone latent sequence to produce the frame-level hidden state sequence \(\text{ms} \in \mathbb{R}^{C_s \times W}\) that encompasses all the information provided by the musical score.

3) Diffusion Decoder: The architecture of the decoder \(G_0(\mathbf{x}_t, t, \text{ms}, \text{id})\) is similar to that of [9], [18], which is essentially a stacked non-causal conditional WaveNet [1] as illustrated in Fig. 2b. With time step condition \(t\) encoded through a sinusoidal embedding module followed by a stack of two dense layers with sigmoid linear unit (SiLU) [29] non-linearity, the diffusion decoder estimates a clean Mel-spectrogram \(\hat{x}_{0,t}\) from the \(t\)-step noised input \(x_t\) conditioned on musical score information \(\text{ms}\). The estimated clean Mel-spectrogram is then noised through Equation 5 to complete the \(p_0(\hat{x}_{0,1}|x_t)\) generation process stated by Equation 3.

B. Musical-Score-Conditioned Discriminator

The Musical-Score-Conditioned (MSC)-discriminator \(D_0(\mathbf{x}_t, \mathbf{x}_t, t, \hat{s}_{\text{pho}}, \hat{s}_{\text{len}}, s_{\text{pit}}, \text{id})\)’s backbone is 2D residual convolutional blocks (ResBlock), which are grouped and connected as depicted in Fig. 3a.

1) Residual Block: The Residual Block (ResBlock) illustrated in Fig 3b has two variants: the conditional ResBlock and the unconditional ResBlock. To adapt to the varying level of noise, a time step vector is projected through a dense layer and added to the residual latent features. For conditional blocks, the singer identity vector and the adaptive-interpolated encoded musical score sequence condition the residual latent features through the Locally-Biased Modulation (LB-mod) algorithm.

2) Locally-Biased Modulation: The Locally-Biased Modulation (LB-mod) algorithm in the conditional ResBlock was inspired by [30] but differs from it in preserving the temporal dimension. LB-mod takes the adaptive-interpolated encoded musical score \(\mathbf{ms} \in \mathbb{R}^{C_s \times W}\), the singer identity vector \(\mathbf{v} \in \mathbb{R}^{C_s \times 1}\), and the latent features \(\mathbf{y} \in \mathbb{R}^{C_h \times W}\).

With two dense layers, LB-mod first projects and combines \(\mathbf{ms}\) and \(\mathbf{v}\) to produce the condition sequence \(s \in \mathbb{R}^{2C_s \times W}\) as in Equation 14:

\[
s_{2C_s \times W} = \text{Dense}_{\text{ms}}^{C_s \rightarrow 2C_s}(\mathbf{ms}) + \text{Dense}_{\text{id}}^{C_s \rightarrow 2C_s}(\mathbf{v})
\]

Subsequently, the modulation is performed as a linear-transform-and-bias operation defined in Equation 15:

\[
\mathbf{LB-Mod}(s_{C_h \times W}^2, s_{2C_h \times W}^2) := s_{1:C_h \times W}^2 \odot \mathbf{y} + s_{C_h+1:2C_h}^2,
\]

where \(s_{2C_h \times W}^2\) is \(s_{C_h \times W}^2\) reshaped by expanding and repeating along the second dimension.

C. Training Objective

The training objective of the acoustic model generator contains three elements: the duration loss, the reconstruction loss, and the adversarial loss.

In the training process, the ground truth phone durations \(D_{1 \times L_p}\) are used, while the estimated durations \(\mathbf{D}_{1 \times L_p}\) are used in the inference stage. Therefore, the variance adaptor returns both the encoded musical score information and the estimated duration sequence, for which a mean-square-error (MSE) is taken against the ground truth duration sequence:

\[
\mathcal{L}_{\text{dur}} := \| \mathbf{D} - \mathbf{\hat{D}} \|_2.
\]

The diffusion decoder’s Mel-spectrogram reconstruction loss is calculated as the L1-distance between \(x_0\) and \(\hat{x}_{0,1}\):

\[
\mathcal{L}_{\text{recon}} := \| x_0 - \hat{x}_{0,1} \|_1.
\]

With the adversarial loss defined by Equation 13, the acoustic model generator parameters \(\theta\) are updated with gradients calculated with the weighted sum of the three objectives:

\[
\mathcal{L}_G = \mathcal{L}_{\text{dur}} + \lambda_{\text{recon}} \mathcal{L}_{\text{recon}} + \lambda_{\text{adv}} \mathcal{L}_{\text{adv}}.
\]

The weight for the reconstruction loss \(\lambda_{\text{recon}}\) and the adversarial loss \(\lambda_{\text{adv}}\) were both set to 1.0 for the default mixed setup. For the WGAN-only setup in the later experiment section, \(\lambda_{\text{recon}}\) was set to 0.

D. HiFi-GAN Neural Vocoder

As the backend audio synthesizer for our SVS system, HiFi-GAN [11] was chosen for its compute efficiency, state-of-the-art synthesis audio quality, and robustness shown across multiple related works [8], [9], [22], [28]. For our implementation and experiments, HiFi-GAN v2 was adopted with the number of initial channels modified to 256.

After HiFi-GAN was pre-trained on the Mpop600 dataset, it was fine-tuned to mitigate the discrepancies between real and synthesized Mel-spectrograms. In the last 35k steps of acoustic model training, the pre-trained HiFi-GAN vocoder was loaded and trained with the estimated Mel-spectrograms of the Diff-WGAN acoustic model stochastically mixed into

2https://github.com/jik876/hifi-gan
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(a) The overall architecture of the MSC-discriminator.

(b) The ResBlock architecture of the MSC-discriminator

Fig. 3: Fig 3a: The overall architecture of the MSC-discriminator. Fig 3b: The internal architecture of the Conditional-ResBlocks used by the MSC-discriminator. The modules to the right of the dashed line are all block-dependent modules/operations. Unconditional-ResBlocks takes the same architecture, but no Singer Identity Vector and Musical Score information is provided and LB-mod is not performed. (H, W: the dimensions of the input downsampled from $M \times L_f; C_s, C_v$: channel dimensions of the singer identity vector and the encoded musical score respectively. Other symbols are defined the same as in Fig. 2a)

their training data according to the probability density function defined in Equation 19:

$$Pr[\text{replace } x_0 \text{ with } \hat{x}_{0,t}] = (1 - \frac{t - 1}{T})^2.$$  \hspace{1cm} (19)

IV. EXPERIMENTS

A. Dataset

All the experiments in this work were conducted with our lab’s Mpop600 Mandarin singing voice dataset [31]. The Mpop600 dataset contains the singing voices of two female and two male singers. Each singer contributed 3 hours of singing voice audio consisting of 150 different song excerpts. In total, the entire Mpop600 dataset is 12-hour-long with 600 song excerpts. All the songs in this dataset were pop-music sung in Mandarin and recorded without background instruments. The audio and phone-transcribed lyrics were forced-aligned to frame-level by the open-source Speech-Aligner\(^3\), the details of which can be found in our previous work [14], [31]. For all the experiments, the audio recordings were down-sampled from 96 kHz, 24-bits to 22.05 kHz, 16-bits.

For evaluation, two song excerpts from each singer’s 150 song excerpts were reserved and not seen by the model in the training process. To train the models with mini-batches, every song excerpt was segmented into smaller audio samples with audio durations of 6 to 12 seconds.

\(^3\)https://github.com/open-speech/speech-aligner

B. Training Setup

The experiments were conducted with audio samples produced through the following setups:

- **Reference**: ground truth Mpop600 audio samples sung by human singers down-sampled to 22.05 kHz.
- **Resynthesized**: ground truth audio samples converted to Mel-spectrograms and re-synthesized by the HiFi-GAN vocoder at 22.05 kHz sample rate.
- **model-FFT**: an end-to-end SVS system with a Feed-forward Transformer backbone as the acoustic model decoder trained on an L1 Mel-spectrogram estimation loss.
- **model-Diff-L1 ($T = 4$)**: the proposed system with the DDPM acoustic model trained exclusively on the L1 Mel-spectrogram reconstruction loss without WGAN.
- **model-Diff-Mixed ($T = 4$)**: the proposed system with the DDPM acoustic model trained with both the L1 Mel-spectrogram reconstruction loss and the WGAN adversarial loss.
- **model-Diff-WGAN ($T = 4$)**: the proposed system with the DDPM acoustic model trained exclusively by WGAN without the L1 Mel-spectrogram reconstruction loss.

All the end-to-end synthesis models utilized the HiFi-GAN vocoder for waveform generation and Mel-spectrograms as the acoustic features. The experimented acoustic models were trained by an AdamW [32] optimizer with L2 weight decay of $10^{-6}$ while the the HiFi-GAN vocoder was pre-trained with
TABLE II: Objective evaluation results of different systems.

| System      | MS-SSIM ↑ | MCD ↓ | F0-RMSE ↓ | F0-Corr ↑ |
|-------------|-----------|-------|-----------|-----------|
| Re-synthesized | 0.985    | 2.613 | 0.273     | 0.936     |
| FFT         | 0.756    | 8.206 | 0.628     | 0.751     |
| Diff-L1     | 0.899    | 5.702 | 0.411     | 0.882     |
| Diff-Mixed  | 0.879    | 6.348 | 0.463     | 0.881     |
| Diff-WGAN   | 0.886    | 6.130 | 0.438     | 0.878     |

TABLE III: Mean Opinion Score (MOS) evaluation results of different systems collected on 10 human participants.

| System       | MOS Score (1 ~ 5) |
|--------------|-------------------|
| Reference    | 4.76 ± 0.099      |
| Re-synthesized | 4.15 ± 0.243    |
| model-FFT    | 2.55 ± 0.447      |
| model-Diff-L1 | 3.79 ± 0.242    |
| model-Diff-Mixed | 3.49 ± 0.481  |
| model-Diff-WGAN | 2.88 ± 0.279  |

indicates best in terms of "naturalness concerning human singers". Two samples from each of the four singers were used in the MOS test. The MOS data are presented in Table III with their 95% confidence intervals.

E. Preference Test on Musical Expressiveness

To particularly examine the proposed Diff-WGAN architecture’s effects on musical expressiveness, model-Diff-L1 and model-Diff-WGAN were subjected to a preference test with 20 participants. Four extra audio segments were sampled from the validation set of the two skilled singers (one male and one female) who exhibit more complex variations musically. The audio samples were formulated into four questions. In each question, the human participants had to choose the sample they deemed more musically expressive disregarding pronunciation accuracy or audio quality or choose the No Preference option if they deemed the two on par. The result of the preference test is shown in Fig 4.

Fig. 4: Musical expressiveness preference test results on 20 participants.

V. DISCUSSION AND ANALYSIS

A. Discussion on Quantitative Evaluation Results

In Table III’s MOS test results, model-Diff-L1 received the highest score. Looking at the measurements presented in Table II, model-Diff-L1’s advantage can likely be attributed to its reconstructive L1 objective. Since its target was only to best-estimate the ground truth Mel-spectrograms in the L1 distance, model-Diff-L1 naturally had a low overall distortion to the ground truth, as evident from the objective measurements. This attribute means model-Diff-L1 robustly produces the high-energy spectral features that mimic those produced by human singers and rids the synthesized Mel-spectrograms of significant artifacts that greatly impact the perceived quality of an audio segment in the singing voice context.
In comparison, model-Diff-Mixed and model-Diff-WGAN’s objectives were not to estimate the ground truth Mel-spectrograms but their generation distributions; therefore, the generator was enforced to also reproduce the variations and inconsistencies of human singers. However, in the context of sung music, human listeners give audio samples with any artifacts or errors in pitch or pronunciation significantly lower scores regardless of the rest of their properties. Hence, the less consistent Diff-WGAN-based models received lower scores in both the objective measurements and the MOS test.

Nevertheless, model-Diff-WGAN crucially beats model-Diff-L1 in the musical expressiveness preference test. While the best strategy for model-Diff-L1 to optimize for reconstruction objectives was to over-smooth these variations, model-Diff-WGAN optimized towards the data distribution estimated by the acoustic model discriminator, which injects variations and details not just acoustically but also on meta-features as musical expression. This observation is further investigated in the following qualitative study.

**B. Qualitative Study on Generated Mel-Spectrograms**

Based on these observations, it can be concluded that the WGAN has indeed prevented the acoustic model from over-smoothing, but the variations it introduced also made the acoustic model less consistent and prone to error. As human listeners are intolerant to errors in music, further investigations have to be made to leverage the correctness enforced by the reconstruction objective and the spectral details and expressiveness brought about by the WGAN.

**C. Remark on Training Stability and Convergence**

One of the key advantages of the proposed combination of DDPM and WGAN is its stability. In the training process, the discriminator loss of the Diff-WGAN acoustic models Wasserstein decreased monotonically, and no mode collapse has been encountered in the experimented configurations even for model-Diff-WGAN, in which no reconstruction loss was employed as constraint or guidance.

**VI. CONCLUSIONS**

This work proposed an acoustic model based on a combined architecture of diffusion denoising probabilistic model (DDPM) and Wasserstein generative adversarial network (WGAN). To exploit the singing voice synthesis (SVS) formulation, the discriminator was designed to be conditioned not only on the synthesis features but also on the musical score and singer identity. This proposed acoustic model architecture was implemented with an integrated HiFi-GAN vocoder to form a multi-singer end-to-end singing voice synthesis system trained on the Mpop600 Mandarin singing voice dataset. Although the proposed architecture was not fully exploited to comprehensively outperform the baseline diffusion model, the preference test and the qualitative study suggested that the addition of WGAN fulfilled its purpose of prompting musical expressiveness and enforcing high-frequency acoustic details. Moreover, this adversarial acoustic model was shown to converge without the reconstruction objective as guidance, thereby proving the convergence and stability of the proposed Diff-WGAN architecture.
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