UNIVERSAL ADAPTOR: CONVERTING MEL-SPECTROGRAMS BETWEEN DIFFERENT CONFIGURATIONS FOR SPEECH SYNTHESIS

Fan-Lin Wang¹, Po-chun Hsu*,², Da-rong Liu*,², Hung-yi Lee¹²

¹Department of Electrical Engineering, National Taiwan University, Taiwan
²Graduate Institute of Communication Engineering, National Taiwan University, Taiwan

ABSTRACT

Most recent speech synthesis systems are composed of a synthesizer and a vocoder. However, the existing synthesizers and vocoders can only be matched to acoustic features extracted with a specific configuration. Hence, we can’t combine arbitrary synthesizers and vocoders together to form a complete system, not to mention apply to a newly developed model. In this paper, we proposed Universal Adaptor, which takes a Mel-spectrogram parametrized by the source configuration and converts it into a Mel-spectrogram parametrized by the target configuration, as long as we feed in the source and the target configurations. Experiments show that the quality of speeches synthesized from our output of Universal Adaptor is comparable to those synthesized from ground truth Mel-spectrogram no matter in single-speaker or multi-speaker scenarios. Moreover, Universal Adaptor can be applied in the recent TTS systems and voice conversion systems without dropping quality.

Index Terms— speech synthesis, text-to-speech, voice conversion, vocoder

1. INTRODUCTION

Neural speech synthesis has achieved remarkable audio qualities recently [1]. Most speech synthesis systems comprise two cascaded separated modules: synthesizer and vocoder. For instance, in text-to-speech (TTS), the synthesizer takes text as input and outputs an audio mid-representation. In voice conversion (VC), the synthesizer takes a source speaker’s audio as input and outputs a target speaker’s audio mid-representation. Such a representation is typically chosen because it is easier to model than raw audio while preserving enough information to allow faithful inversion back to audio. In this paper, we follow the most popular works [1, 2, 3, 4, 5, 7, 8, 9] to choose Mel-spectrogram as the mid-representation. Then in the second module, the vocoder takes the mid-representation as input and outputs the final waveform. The vocoder is required to be expressive enough to model the raw audio, which has short- and long-term dependencies at different timescales.

Ideally, the development of the synthesizer and the vocoder can be totally disentangled. For example, if an author proposes a new vocoder, it should be able to combine with each existing synthesizer directly, and most of them can be found with source codes and pretrained models. However, we find that these pretrained models may be trained on acoustic features extracted with different speech configurations. For instance, one of the most popular public implementations of Tacotron 2 is conditioned on Mel-spectrograms with a hop size of 275 and a frequency range [55, 7600]. In contrast, another implementation sets the hop size as 256 and the frequency range as [0, 8000]. This forces the author to either train the proposed vocoder according to different corresponding speech configurations or retrain all synthesizers according to the vocoder’s configuration. Both methods take extra time and computing resources, which may be critical for the research groups with limited resources. A similar situation occurred when developing a new synthesizer.

Within the configuration mismatch, some parameters can be fixed by closed-form math conversion, such as elementary arithmetic or log operation. However, other configurations cannot be simply conversed. Therefore, a trainable adaptor is required to close the gap. Some studies have similar objectives, such as speech bandwidth expansion (BWE) [19, 20].

1https://github.com/Rayhane-mamah/Tacotron-2
2https://github.com/NVIDIA/tacotron2
Table 1. All target configurations supported in Universal Adaptor. (a) non-normalizable: parameters without closed-form math conversion; (b) normalizable: parameters with closed-form math conversion.

| Parameter        | Value                                      |
|------------------|--------------------------------------------|
| (a) non-normalizable |
| wave peak norm   | [0.9∼1.0]                                  |
| n_fft            | [1024, 2048]                               |
| win_length       | [800, 900, 1024, 1100, 1200]               |
| hop length       | [window length/4]                          |
| left pad         | [0, (n_fft-win_length/4)/2]                |
| right pad        | [0, (n_fft-win_length/4)/2]                |
| fmin             | [0, 30, 50, 70, 90]                        |
| fmax             | [7600, 8000, 9500, 11025]                  |
| (b) normalizable  |
| normalize mel    | [True, False]                              |
| ref_level_db     | [0]                                        |
| min_level_db     | [-100]                                     |

BWE aims to compensate the high-frequency part of a speech signal to increase its resolution. Researchers usually train a deep neural network to perform BWE. Nevertheless, each BWE model can only upsample the signal to its assigned sampling rate, which is not useful when facing arbitrary frequency range, not to mention other time-domain configurations.

To solve the issues, we proposed **Universal Adaptor**, which can convert a Mel-spectrogram between any two configurations. With Universal Adaptor, we can cascade any off-the-shelf synthesizer and vocoder even if they are trained with different speech configurations, which is illustrated in figure 1. We also demonstrated that Universal Adaptor can be used in any applications involving speech syntheses such as TTS and VC. Most importantly, there is no performance drop when we cascade models with Universal Adaptor. Therefore, Universal Adaptor can help determine a vocoder and cascade with any synthesizer for a fair comparison. In Section 2.1 we first described the architecture design of Universal Adaptor. Then in Section 2.2, we evaluated the effectiveness of Universal Adaptor on different combinations of synthesizers and vocoders. Throughout the experiments, all synthesizers and vocoders are collected from pretrained models from open sources. Except for Universal Adaptor, no additional training is required. Finally, we concluded our paper in Section 4.

2. UNIVERSAL ADAPTOR

Universal Adaptor takes three inputs: the source speech configuration $cfg_{src}$, the target speech configuration $cfg_{tgt}$, and the source Mel-spectrogram $Mel_{src}$ parametrized by $cfg_{src}$. Then, the adaptor generates the target Mel-spectrogram $Mel_{tgt}$ parametrized by $cfg_{tgt}$. In this paper, we support any arbitrary $cfg_{src}$ and any $cfg_{tgt}$ listed in Table 1 which includes most of the common parameters. Specifically, all configurations are categorized into two: normalizable and non-normalizable. The normalizable configurations include those which have simple closed-form math conversion among different choices. For example, there is a simple closed-form conversion between the Mel-spectrogram that has log base 10 and $e$: simply multiplying or dividing by $\ln 10$. On the other hand, the non-normalizable configurations cover the rest of the parameters that can not simply be conversed. Universal Adaptor includes two stages as shown in Figure 2, which are described in Sections 2.1 and 2.2 respectively.

2.1. Stage 1: Approximate conversion

In this stage, we take inputs $cfg_{src}$, $cfg_{tgt}$ and $Mel_{src}$, and generate the ‘approximate’ target Mel-spectrogram $Mel_{tgt}$. In detail, $Mel_{src}$ is first approximately transformed back to the linear spectrogram, which is done by multiplication to the pseudo inverse matrix of the Mel-scale filter-bank. Then we reconstruct the intermediate waveform from the linear spectrogram by Griffin-Lim algorithm [24]. The algorithm is iterated for 32 times. Afterwards, the waveform is used to generate the $Mel_{tgt}$ according to $cfg_{tgt}$ with the standard Mel-spectrogram extraction pipeline. It is worth noting that there are no trainable modules included in this stage. Because the inversion of the Mel-spectrogram to the linear spectrogram and Griffin-Lim algorithm are only approximations, the reconstructed intermediate waveform and $Mel_{tgt}$ only have low quality. Therefore, stage 2 is added to further boost the feature quality.
2.2. Stage 2: Post processing

In this stage, we take $cfg_{tgt}$ and $Mel_{tgt}'$ as input and generate the final target Mel-spectrogram $Mel_{tgt}$. The core module of this stage is a U-Net \([25-27]\). Before inputting $Mel_{tgt}'$ into the U-Net, we normalize $Mel_{tgt}'$ according to the normalizable configurations of $cfg_{tgt}$, $cfg_{tgt}(b)$, and denoted the normalized Mel-spectrogram as $Mel_{tgt}'^N$. The normalizing base is shown in Table 1(b). Then after obtaining the output of the U-Net, we de-normalize the output, which is $Mel_{tgt}$, according to $cfg_{tgt}(b)$ and get the final $Mel_{tgt}$. The reason for normalization is that for each configuration, the Mel-spectrogram is on different scale, and the range of quantity is very large. Therefore, the size of loss will be mostly dependent on the scale of Mel-spectrogram instead of the recovery ability of U-Net. In order to stabilize the training, we only leave U-Net to model the non-normalizable part.

The U-Net module takes $Mel_{tgt}'^N$ and the non-normalizable configuration of $cfg_{tgt}$, denoted as $cfg_{tgt}(a)$, as input. The whole architecture is illustrated in Figure 3(a), which consists of an encoder (left side) and a decoder (right side). The encoder contains stacks of adaptive ConvBlocks (described in the next paragraph) and Max Pooling layers, which downsample the feature map and increase the number of feature channels; the decoder contains stacks of adaptive ConvBlocks and transposed convolution layers, which upsample the feature map and meanwhile decrease the number of feature channels. There are residual connections between the encoder and the decoder at each corresponding block, including the input and the output.

The adaptive ConvBlock, illustrated in Figure 3(b), is a convolution block that contains an adaptive linear layer \([28]\) parameterized by $cfg_{tgt}(a)$. The layer is sandwiched between a typical convolutional neural network structure (2D convolution, batch normalization, and rectified linear unit function). More specifically for the details, $cfg_{tgt}(a)$ is first encoded as an 8-dimensional vector $C$. In $cfg_{tgt}(a)$, $f_{min}$ and $f_{max}$ means the lower bound and upper bound of frequency for Mel basis, and the others are all common arguments in short-time Fourier transform (STFT). For values with a wider range such as the hop length and win length, we use the logarithm of the value, while simply use the original value of the others shown in Table 1(a). Then $C$ determines the weight and the bias of the adaptive linear layer:

$$W = Linear(C), \quad b = Linear(C). \quad (1)$$

After we obtain the weight and the bias, the vector goes through a nonlinear activation function. Therefore, the complete function of the adaptive linear layer is as follows:

$$X' = PReLU(WX + b) \quad (2)$$

3. EXPERIMENTS

3.1.Datasets

Our adaptor was trained on LibriTTS \([29]\), a multi-speaker English corpus derived from the original materials of LibriSpeech \([30]\) and often used in speech synthesis tasks \([31-34]\). We downsampled the utterances to 22kHz for training. As for the test set, we considered a single-speaker and a multi-speaker dataset. The former is the most commonly used single-speaker dataset, LJSpeech \([35]\), consisting of short audio clips of a single speaker reading non-fiction book passages. The other is the CMU-ARCTIC databases \([36]\), which were constructed as phonetically balanced, US English speaker databases designed for unit selection speech synthesis research. We chose two male and female speakers for the multi-speaker experiment in Section 3.5 and all seven speakers for the voice conversion experiment in Section 3.6.

3.2. Training setup

In the training phase, we used the AdamW \([37]\) optimizer with default parameters. The learning rate starts from $1e-3$ and halves every 50 epochs. U-Net contains 4 layers in the encoder and the decoder respectively, and was trained for 100 epochs with a batch size of 32 on 200-frame long segments. 10% of the training data were randomly chosen for validation.
| Source | Target | WaveRNN (cfg1) | WaveGlow (cfg2) | HiFiGAN (cfg3) | MelGAN (cfg4) |
|--------|--------|---------------|----------------|---------------|---------------|
|        |        | inter.        | inter.         | inter.        | inter.        |
|        |        | Griffin.      | Griffin.       | Griffin.      | Griffin.      |
|        |        | adapt.        | adapt.         | adapt.        | adapt.        |
|        |        | MCD           |                |               |               |
| cfg1   |       | -             | 9.68           | 9.14          | 48.17         | 17.66         | 15.15         | 49.88         | 10.00         | 7.97          | 23.02         | 13.78         | 10.13         |
| cfg2   |       | 49.99         | 32.92          | 12.48         | -             | 9.73          | 9.39          | 8.97          | 6.31          | 5.06          | 38.26         | 26.30         | 10.78         |
| cfg3   |       | 49.86         | 33.15          | 12.73         | 11.87         | 9.99          | 9.33          | -             | 5.95          | 4.78          | 37.46         | 26.24         | 10.56         |
| cfg4   |       | 17.55         | 9.96           | 9.04          | 41.21         | 10.97         | 9.73          | 43.94         | 6.33          | 5.08          | -             | 8.23          | 6.48          |
|        |        |                |                |               |                |                |                |                |                |                |                |                |                |
| F0-RMSE|        |                |                |               |                |                |                |                |                |                |                |                |                |
| cfg1   |       | -             | 6.36           | 7.45          | 50.18         | 11.63         | 9.28          | 44.63         | 8.94          | 8.55          | 27.98         | 8.15          | 7.20          |
| cfg2   |       | 56.32         | 24.77          | 6.19          | -             | 7.98          | 6.61          | 9.98          | 6.09          | 4.94          | 26.74         | 7.31          | 5.45          |
| cfg3   |       | 58.26         | 19.15          | 7.05          | 7.72          | 8.28          | 7.93          | -             | 5.36          | 4.50          | 26.60         | 7.22          | 6.12          |
| cfg4   |       | 31.58         | 6.12           | 7.05          | 23.63         | 8.96          | 6.07          | 26.56         | 5.70          | 7.05          | -             | 5.11          | 4.83          |

| V/UV Error|        |                |                |                |                |                |                |                |                |                |                |                |                |
| cfg1   |       | -             | 5.93           | 6.14          | 14.37         | 9.31          | 8.63          | 14.52         | 9.70          | 8.85          | 15.62         | 11.37         | 6.17          |
| cfg2   |       | 13.38         | 10.34          | 7.67          | -             | 6.16          | 5.67          | 7.96          | 7.05          | 5.67          | 10.53         | 7.27          | 5.58          |
| cfg3   |       | 12.87         | 11.26          | 7.47          | 8.23          | 5.40          | 6.56          | -             | 5.70          | 4.53          | 7.62          | 8.20          | 6.41          |
| cfg4   |       | 15.98         | 6.86           | 5.46          | 8.52          | 7.34          | 7.12          | 7.40          | 5.29          | 4.83          | -             | 6.19          | 3.90          |

Table 2. Objective evaluation results (MCD, F0-RMSE, V/UV Error) of different models. (inter.: interpolation; Griffin.: Griffin-Lim; adapt.: Universal Adaptor)

| Parameter | cfg1 | cfg2 | cfg3 | cfg4 | cfg5 | cfg6 | cfg7 |
|-----------|------|------|------|------|------|------|------|
| wave peak norm | 1.0  | 1.0  | 1.0  | 0.95 | 1.0  | 0.95 | 1.0  |
| n_fft | 2048 | 1024 | 1024 | 1024 | 2048 | 1024 | 1024 |
| win_length | 1100 | 1024 | 1024 | 1024 | 1200 | 1024 | 465  |
| hop_length | 275  | 256  | 256  | 256  | 300  | 240  | 160  |
| left pad | 0    | 0    | 384  | 384  | 0    | 392  | 0    |
| right pad | 0    | 0    | 384  | 384  | 0    | 392  | 0    |
| fmin | 40   | 0    | 0    | 0    | 0    | 0    | 80   |
| fmax | 11025 | 8000 | 8000 | 11025 | 12000 | 8000 | 8000 |
| amp_to_db | True | True | True | True | True | True | False |
| log_base | 'e'  | 'e'  | 'e'  | 10   | 10   | 'e'  | 'e'  |
| log_factor | 20   | 1    | 1    | 20   | 1    | 1    | 1    |
| normalize mel | False | False | False | False | False | False | False |
| ref_level_db | 0    | -    | -    | -    | -    | -    | -    |
| min_level_db | -100 | -    | -    | -    | -    | -    | -    |

Table 3. All the configurations we used in the experiments. Only the important parameters are listed in the table.

Theoretically for training, we should randomly sample a source/target configuration pair for each utterance. However, Griffin-Lim algorithm produces a computation bottleneck in training. Therefore, in order to speed up training, we performed Griffin-Lim algorithm beforehand. Before training, we randomly divided all of the training utterances into 100 subsets and generated a configuration served as cfgsrc for each subset. cfgsrc is fixed throughout the training process. Each subset is then precomputed into intermediate waveforms, which is illustrated in stage 1 of Figure 2 according to the corresponding cfgsrc. During training, we randomly generated 100 configurations in each epoch, and randomly sampled a configuration for each intermediate waveform to serve as cfgtgt. The ground-truth Mel-spectrogram is computed accordingly from the original waveform. It is worth mentioning that while producing configurations, including cfgsrc and cfgtgt, we avoided the configurations we used for testing in the following experiments to demonstrate the generalization of the proposed method.

With regards to the loss function, we used L1-loss between Meltgt illustrated in Figure 2 and the ground-truth Mel-spectrogram instead of the commonly used L2-loss. We found that the error between the Meltgt and the ground-truth is very small in general. If L2-loss is used, the loss will be too small and suffer from gradient vanishing. All codes and audio samples will be publicly available online.

### 3.3. Configuration pairs

In our single-speaker experiments, we used four vocoders: WaveRNN [10], WaveGlow [11], HiFiGAN [13], and MelGAN [12]. These four are matched to each specific configuration. We named their configurations as cfg1, cfg2, cfg3, and cfg4, respectively. Besides, three pretrained synthesizers were adopted in our TTS experiments, and cfg1 is also the configuration for Tacotron 2 [5]; cfg2 is that for Tacotron 2 [5]; cfg3 is that for FastSpeech 2 [4]. In the VC experiments, another three pretrained synthesizers were adopted. The configuration of AdaIN-VC [7] is denoted by cfg6; that of PPG-VC [22] is denoted by cfg7. The official repositories provide a vocoder for PPG-VC, PPG-Voc (cfg6), and a vocoder for S2VC, S2VC-Voc (cfg7). Note that the official AdaIN-VC uses only the Griffin-Lim algorithm to restore the waveform. All of the seven configurations are listed in Table 5. In all the tables of experiment results, the row represents cfgsrc of the input of Universal Adaptor, and the column represents cfgtgt of the input of the vocoder.

---

3https://falijhwang.github.io/Universal-Adaptor/demo/demo.html
Table 4. MOS results of different models when using acoustic features from LJSpeech ground truth utterances. The scores are reported with 95% confidence intervals. In the Orig. rows, \( c_{fg_{src}} \) is same as \( c_{fg_{tgt}} \), but the Mel-spectrogram does not go through Universal Adaptor.

| Source | Target | WaveRNN \((c_{fg1})\) | WaveGlow \((c_{fg2})\) | HiFiGAN \((c_{fg3})\) | MelGAN \((c_{fg4})\) |
|--------|--------|----------------|----------------|----------------|----------------|
| LJSpeech (MOS: 4.45±0.12) |
| \( c_{fg1} \) | 3.89±0.147 | 2.67±0.192 | 4.13±0.143 | 2.69±0.158 |
| \( c_{fg2} \) | 3.82±0.160 | 2.86±0.183 | 4.16±0.132 | 2.80±0.163 |
| \( c_{fg3} \) | 3.77±0.159 | 2.82±0.184 | 4.22±0.132 | 2.70±0.156 |
| \( c_{fg4} \) | 3.40±0.152 | 2.78±0.190 | 4.20±0.138 | 2.83±0.179 |
| Orig. | 3.70±0.163 | 2.97±0.187 | 4.31±0.136 | 2.62±0.167 |

Table 5. MOS results of HiFiGAN trained on VCTK [38] and tested on acoustic features from CMU_ARCTIC. The scores are reported with 95% confidence intervals. In the Orig. rows, \( c_{fg_{src}} \) is same as \( c_{fg_{tgt}} \), but the Mel-spectrogram does not go through Universal Adaptor.

| Source | Target | HiFiGAN \((c_{fg3})\) |
|--------|--------|----------------|
| \( c_{fg1} \) | 3.55±0.150 |
| \( c_{fg2} \) | 3.63±0.168 |
| \( c_{fg3} \) | 3.34±0.172 |
| \( c_{fg4} \) | 3.58±0.176 |
| Orig. | 3.51±0.149 |
| Ground Truth | 3.97±0.152 |

output which is also the configuration of the vocoder.

3.4. Objective evaluation

For objective evaluation, we picked three aspects to investigate: 1. Mel-ceptral distortion (MCD), which is to measure the difference between two sequences of Mel-cepstra; 2. F0-RMSE, which is the root mean square error of fundamental frequency between two waveforms; 3. V/UV error, which is the error rate of the voiced and the unvoiced flags between the generated and the reference speech. The metrics are calculated in comparison to the reference waveforms synthesized from ground-truth Mel-spectrograms.

We compared our proposed method (the columns denoted adapt.) to two baselines. The first baseline is closed-form math conversion. We interpolated Mel\(_{src}\) to match with the hop length of Mel\(_{tgt}\) and rescaled Mel\(_{src}\) by the normalizable parameters of Mel\(_{tgt}\). Finally, we synthesized the waveforms from them (the columns denoted inter.). The second baseline is Griffin-Lim algorithm. We synthesized waveforms from Mel\(_{tgt}\), which is the output of the first stage of Universal Adaptor (the columns denoted Griffin.).

The results are shown in Table 2. Scores with identical \( c_{fg_{src}} \) and \( c_{fg_{tgt}} \) are shown with gray backgrounds and reported as the top lines for different vocoders. Note that interpolation takes no effect on Mel\(_{src}\) when \( c_{fg_{src}} \) and \( c_{fg_{tgt}} \) are the same. We first see that the scores in \textit{inter.} are apparently much higher than the other scores, which means pure interpolation is not enough to fix the configuration mismatch. We can hear from the audio samples that the main distortion comes from the frequency bandwidth mismatch. If the band is narrower in \( c_{fg_{src}} \) than that in \( c_{fg_{tgt}} \), the pitch of the speech will shift higher, and vice versa. It is because the distribution of the frequency band in Mel\(_{src}\) is different from that in Mel\(_{tgt}\), which can cause a misunderstanding by the vocoder.

Moreover, when \( c_{fg_{src}} \) and \( c_{fg_{tgt}} \) are the same, the errors in \textit{inter.} should be zero, except for WaveRNN, which clips the Mel-Spectrogram and causes a difference in rescaling, as well as WaveGlow, which inputs random noises.

On the other hand, the scores in \textit{adapt.} have an obvious improvement in most of the combinations comparing to \textit{Griffin}. That is, our second stage can effectively enhance the quality of Mel\(_{tgt}\). Furthermore, for conversions with different \( f_{max} \) in source and target configurations, such as \( c_{fg2} \) to \( c_{fg1} \), the proposed method can restore the high-frequency information of Mel\(_{tgt}\) and leads to lower MCD results.

3.5. Subjective evaluation

For subjective evaluation, we performed the Mean Opinion Score (MOS) tests. We randomly chose 15 utterances from the test sets and synthesized the waveforms in all possible configuration combinations. The raters listened to each utterance and rated pleasantness on a five-point scale. Each file was rated by at least 10 different raters.

In this subsection, there are two parts of experiments, single-speaker experiment on LJSpeech and multi-speaker experiment on CMU_ARCTIC. In the experiments, the input of Universal Adaptor is the Mel-spectrogram extracted from ground truth waveforms. It is worth mentioning that in the Orig. rows of Table 4 and 5 the Mel-spectrograms do not go through Universal Adaptor. \( c_{fg_{src}} \) is matched to \( c_{fg_{tgt}} \). The Orig. scores can be the reference of the original performance. In addition, we added the ground truth waveform as a topline. The corresponding scores were written in LJSpeech row in Table 4 and in Ground Truth row in Table 5.

The results of the single-speaker experiment are shown in
Table 6. MOS results of different models when using acoustic features from single-speaker TTS models trained on LJSpeech. The scores are reported with 95% confidence intervals. In the Orig. rows, $cfg_{src}$ is same as $cfg_{tgt}$, but the Mel-spectrogram does not go through Universal Adaptor.

| Source     | WaveRNN ($cfg_1$) | WaveGlow ($cfg_2$) | HiFiGAN ($cfg_3$) | MelGAN ($cfg_4$) |
|------------|-------------------|--------------------|-------------------|------------------|
| Tacotron ($cfg_1$) | 3.44±0.172       | 2.97±0.151         | 3.63±0.159        | 2.71±0.161       |
| Tacotron 2 ($cfg_2$) | 4.16±0.127       | 3.49±0.167         | 4.34±0.111        | 3.30±0.091       |
| FastSpeech 2 ($cfg_3$) | 3.47±0.158       | 3.34±0.174         | 3.68±0.154        | 2.99±0.172       |
| Orig.      | 3.38±0.144       | 3.32±0.162         | 3.35±0.162        | -                |

Table 7. MOS and similarity results of different models when using acoustic features from voice conversion models trained on VCTK. The scores are reported with 95% confidence intervals. In the Orig. rows, $cfg_{src}$ is same as $cfg_{tgt}$, but the Mel-spectrogram does not go through Universal Adaptor.

| Source     | HiFiGAN ($cfg_3$) | PPG-Voc ($cfg_6$) | S2VC-Voc ($cfg_7$) |
|------------|-------------------|-------------------|-------------------|
| MOS        |                   |                   |                   |
| AdalN-VC ($cfg_5$) | 3.30±0.102 | 3.35±0.099 | 3.26±0.098 |
| PPG-VC ($cfg_6$) | 3.52±0.096 | 3.56±0.089 | 3.34±0.094 |
| S2VC ($cfg_7$) | 3.51±0.094 | 3.52±0.090 | 3.32±0.098 |
| Orig.      | 3.53±0.090       | 3.45±0.093        |                   |

| Similarity |                   |                   |                   |
|------------|-------------------|-------------------|-------------------|
| AdalN-VC ($cfg_5$) | 3.41±0.126 | 3.34±0.129 | 3.28±0.130 |
| PPG-VC ($cfg_6$) | 3.42±0.120 | 3.37±0.125 | 3.40±0.136 |
| S2VC ($cfg_7$) | 3.53±0.124 | 3.47±0.128 | 3.41±0.126 |
| Orig.      | 3.53±0.124       | 3.48±0.117        |                   |

Table 4. Comparing different columns, we can see that Hi-FiGAN is the best vocoder in these four. Rest of three are WaveRNN, WaveGlow, and MelGAN in order. The results comply with original papers [13]. Comparing different rows, we can observe that no matter which source configuration we choose, the results are comparable. It proves that Universal Adaptor is effective for configuration conversion without noticeable distortion. Moreover, observing the grids with gray background leads to that when the input configuration is the same as the output configuration, our adaptor does not corrupt the quality of Mel-spectrograms. Therefore, Universal Adaptor can successfully convert configurations without affecting the vocoder’s performance.

3.6. Speech synthesis applications

We applied Universal Adaptor to two applications, TTS and VC, to demonstrate the effectiveness in real situations. In the experiments, the inputs of Universal Adaptor are Mel-spectrograms generated by the corresponding synthesizers.

The TTS experiment results are shown in Table 6. By comparing the vocoders in the columns, we obtained the same results as those in the last experiment. When we examine different synthesizers, it is obvious that Tacotron 2 stands out, no matter in which column. Furthermore, the results of the gray grids indicated that Universal Adaptor can even slightly improve the quality of Mel-spectrograms.

The VC experiment results are in Table 7. Besides MOS scores, we performed a similarity test on a five-point scale. The vocoders we used are the official vocoders along with Hi-FiGAN pretrained on VCTK. When comparing the MOS scores of vocoders, PPG-Voc performs slightly better than Hi-FiGAN and much better than S2VC-Voc in each row. It is predictable because PPG-Voc has a similar model architecture to Hi-FiGAN and S2VC-Voc is similar to WaveRNN. In addition, no matter using which vocoder, PPG-VC can produce more natural speech than S2VC, but S2VC can produce speech more similar to the target speaker than PPG-VC. AdalN-VC performed the worst in both tests. The results in

On the other hand, the results of multi-speaker experiments are shown in Table 5. The only vocoder we used is Hi-FiGAN ($cfg_3$), which is the only vocoder pretrained on a multi-speaker dataset that is available online among the four vocoders. No matter which source configuration we use, the MOS results are comparable. The results indicate that the proposed Universal Adaptor does not introduce noticeable distortions when converting Mel-spectrograms from multiple speakers.
both experiments indicated that Universal Adaptor can be applied in speech synthesis applications and convert configurations without affecting a model’s performance.

4. CONCLUSIONS

To solve the mismatch of configurations between synthesizers and vocoders, we proposed Universal Adaptor, which includes two stages. The first stage approximately converts the source Mel-spectrogram into the target Mel-spectrogram with poor quality. In the second stage, our module further boosts the quality of the target Mel-spectrogram, which is shown to be effective in objective evaluation. Moreover, the subjective evaluation results revealed that the waveforms synthesized from Universal Adaptor outputs are comparable to those synthesized from ground truth Mel-spectrograms, no matter in single-speaker or multi-speaker scenarios. The result proves the ability of converting configurations of Universal Adaptor. Universal Adaptor can also be applied in the complete TTS systems and VC systems without sacrificing performance, verifying the success of Universal Adaptor.

5. REFERENCES

[1] Kaizhi Qian, Yang Zhang, Shiyu Chang, Xuesong Yang, and Mark Hasegawa-Johnson, “AUTOVC: Zero-shot voice style transfer with only autoencoder loss,” in Proc. ICLR, 2019.

[2] Jheng Hao Lin, Yist Y. Lin, Chung-Ming Chien, and Hung-Yi Lee, “S2VC: A framework for any-to-any voice conversion with self-supervised pretrained representations,” in Proc. Interspeech, 2021.

[3] Isaac Elias, Heiga Zen, Jonathan Shen, Yu Zhang, Ye Jia, R.J. Skerry-Ryan, and Yonghui Wu, “Parallel Tacotron 2: A non-autoregressive neural TTS model with differentiable duration modeling,” in Proc. Interspeech, 2021.

[4] Yi Ren, Chenxu Hu, Xu Tan, Tao Qin, Sheng Zhao, Zhou Zhao, and Tie-Yan Liu, “FastSpeech 2: Fast and high-quality end-to-end text to speech,” in Proc. ICLR, 2021.

[5] Jonathan Shen, Ruoming Pang, Ron J. Weiss, Mike Schuster, Navdeep Jaitly, Zongheng Yang, Zhifeng Chen, Yu Zhang, Yuxuan Wang, Rj Skerrv-Ryan, Rif A. Saurous, Yannis Agiomvrgiannakis, and Yonghui Wu, “Natural TTS synthesis by conditioning WaveNet on mel spectrogram predictions,” in Proc. ICASSP, 2018.

[6] Isaac Elias, Heiga Zen, Jonathan Shen, Yu Zhang, Ye Jia, Ron J Weiss, and Yonghui Wu, “Parallel Tacotron: Non-autoregressive and controllable tts,” in Proc. ICASSP, 2021.

[7] Ju-Chieh Chou, Cheng chieh Yeh, and Hung yi Lee, “One-shot voice conversion by separating speaker and content representations with instance normalization,” in Proc. Interspeech, 2019.

[8] Yist Y Lin, Chung-Ming Chien, Jheng-Hao Lin, Hungyi Lee, and Lin-shan Lee, “FragmentVC: Any-to-any voice conversion by end-to-end extracting and fusing fine-grained voice fragments with attention,” in Proc. ICASSP, 2021.

[9] Yuxuan Wang, R. J. Skerry-Ryan, Daisy Stanton, Yonghui Wu, Ron J. Weiss, Navdeep Jaitly, Zongheng Yang, Ying Xiao, Z. Chen, Samy Bengio, Quoc V. Le, Yannis Agiomvrgiannakis, Robert A. J. Clark, and Rif A. Saurous, “Tacotron: Towards end-to-end speech synthesis,” in Proc. Interspeech, 2017.

[10] Nal Kalchbrenner, Erich Elsen, Karen Simonyan, Seb Noury, Norman Casagrande, Edward Lockhart, Florian Stimberg, Aaron Oord, Sander Dieleman, and Koray Kavukcuoglu, “Efficient neural audio synthesis,” in Proc. ICML, 2018.
[11] Ryan J. Prenger, Rafael Valle, and Bryan Catanzaro, “WaveGlow: A flow-based generative network for speech synthesis,” Proc. ICASSP, 2019.

[12] Kundan Kumar, Rithesh Kumar, Thibault de Boissière, Lucas Gstin, Wei Zhen Teoh, Jose M. R. Sotelo, Alexandre de Brébisson, Yoshua Bengio, and Aaron C. Courville, “MelGAN: Generative adversarial networks for conditional waveform synthesis,” in Proc. NeurIPS, 2019.

[13] Jungil Kong, Jaehyeon Kim, and Jaekyoung Bae, “HiFi-GAN: Generative adversarial networks for efficient and high fidelity speech synthesis,” in Proc. NeurIPS, 2020.

[14] Aaron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew Senior, and Koray Kavukcuoglu, “WaveNet: A generative model for raw audio,” arXiv preprint arXiv:1609.03499, 2016.

[15] Ryuichi Yamamoto, Eunwoo Song, and Jae-Min Kim, “Parallel WaveGAN: A fast waveform generation model based on generative adversarial networks with multi-resolution spectrogram,” in Proc. ICASSP, 2020.

[16] Po-chun Hsu and Hung-yi Lee, “WG-WaveNet: Real-time high-fidelity speech synthesis without GPU,” arXiv preprint arXiv:2005.07412, 2020.

[17] Jean-Marc Valin and Jan Skoglund, “LPCNet: Improving neural speech synthesis through linear prediction,” in Proc. ICASSP, 2019.

[18] Tianren Gao, “Extremely lightweight vocoders for on-device speech synthesis,” M.S. thesis, EECS Department, University of California, Berkeley, May 2021.

[19] Sen Li, Stéphane Villette, Pravin Ramadas, and Daniel J Sinder, “Speech bandwidth extension using generative adversarial networks,” in Proc. ICASSP, 2018.

[20] Archit Gupta, Brendan Shillingford, Yannis Assael, and Thomas C Walters, “Speech bandwidth extension with WaveNet,” in Proc. ICASSP, 2019.

[21] Ju Lin, Yun Wang, Kaustubb Kalgaonkar, Gil Keren, Didi Zhang, and Christian Fuegen, “A two-stage approach to speech bandwidth extension,” in Proc. Interspeech, 2021.

[22] Haohe Liu, Woosung Choi, Xubo Liu, Qiuqiang Kong, Qiao Tian, and DeLiang Wang, “Neural vocoder is all you need for speech super-resolution,” arXiv preprint arXiv:2203.14941, 2022.

[23] Pavel Andreev, Aibek Alanov, Oleg Ivanov, and Dmitry Vetrov, “HiFi++: A unified framework for neural vocoding, bandwidth extension and speech enhancement,” arXiv preprint arXiv:2203.13086, 2022.

[24] Daniel Griffin and Jae 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.

[25] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, “U-Net: Convolutional networks for biomedical image segmentation,” in International Conference on Medical image computing and computer-assisted intervention, 2015.

[26] Da-Yi Wu, Yen-Hao Chen, and Hung yi Lee, “VQVC+: One-shot voice conversion by vector quantization and U-Net architecture,” in Proc. Interspeech, 2020.

[27] H. Kameoka, Takuhiro Kaneko, Kou Tanaka, Nobukatsu Hojo, and Shogo Seki, “VoiceGrad: Non-parallel any-to-many voice conversion with annealed langevin dynamics,” ArXiv, vol. abs/2010.02977, 2020.

[28] Ethan Perez, Florian Strub, Harm de Vries, Vincent Dumoulin, and Aaron C. Courville, “FiLM: Visual reasoning with a general conditioning layer,” in Proc. AAAI, 2018.

[29] H. Zen, V. Dang, R. Clark, Y. Zhang, R. J. Weiss, Y. Jia, Z. Chen, and Y. Wu, “LibriTTS: A corpus derived from LibriSpeech for text-to-speech,” in Proc. Interspeech, 2019.

[30] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, “Librispeech: An ASR corpus based on public domain audio books,” in Proc. ICASSP, 2015.

[31] Po-chun Hsu, Chun-hsuan Wang, Andy T Liu, and Hung-yi Lee, “Towards robust neural vocoding for speech generation: A survey,” arXiv preprint arXiv:1912.02461, 2019.

[32] Rafael Valle, Jason Li, Ryan Prenger, and Bryan Catanzaro, “Mellotron: Multispeaker expressive voice synthesis by conditioning on rhythm, pitch and global style tokens,” in Proc. ICASSP, 2020.

[33] Jaehyeon Kim, Sungwon Kim, Jungil Kong, and Sungroh Yoon, “Glow-TTS: A generative flow for text-to-speech via monotonic alignment search,” in Proc. NeurIPS, 2020.

[34] Rafael Valle, Kevin J. Shih, Ryan Prenger, and Bryan Catanzaro, “Flowtron: an autoregressive flow-based generative network for text-to-speech synthesis,” in Proc. ICLR, 2021.

[35] Keith Ito and Linda Johnson, “The LJ speech dataset,” https://keithito.com/LJ-Speech-Dataset/, 2017.
[36] John Kominek and Alan Black, “The CMU Arctic speech databases,” SSW5-2004, 01 2004.

[37] Ilya Loshchilov and Frank Hutter, “Decoupled weight decay regularization,” in Proc. ICLR, 2019.

[38] Junichi Yamagishi, Christophe Veaux, and Kirsten MacDonald, “CSTR VCTK Corpus: English multi-speaker corpus for CSTR voice cloning toolkit (version 0.92),” 2019.