Abstract—We introduce a novel speech synthesis system, called NAUTILUS, that can generate speech with a target voice either from a text input or a reference utterance of an arbitrary source speaker. By using a multi-speaker speech corpus to train all requisite encoders and decoders in the initial training stage, our system can clone unseen voices using untranscribed speech of target speakers on the basis of the backpropagation algorithm. Moreover, depending on the data circumstance of the target speaker, the cloning strategy can be adjusted to take advantage of additional data and modify the behaviors of text-to-speech (TTS) and/or voice conversion (VC) systems to accommodate the situation. We test the performance of the proposed framework by using deep convolution layers to model the encoders, decoders and WaveNet vocoder. Evaluations show that it achieves comparable quality with state-of-the-art TTS and VC systems when cloning with just five minutes of untranscribed speech. Moreover, it is demonstrated that the proposed framework has the ability to switch between TTS and VC with high speaker consistency, which will be useful for many applications.

Index Terms—voice cloning, text-to-speech, voice conversion, speaker adaptation, neural network.

I. INTRODUCTION

SPEECH synthesis is the technology of generating speech from an input interface. In its narrow sense, speech synthesis is used to refer to text-to-speech (TTS) systems [1], which play an essential role in a spoken dialog system as a way for machine-human communication. In its broader definition, speech synthesis can refer to all kinds of speech generation interfaces like voice conversion (VC) [2], video-to-speech [3], [4], and others [5]. Recent state-of-the-art speech synthesis systems can generate speech with natural sounding quality, some of which is indistinguishable from recorded speech [6]. Deep neural networks are used in various components of these speech synthesis systems. Many use sequence-to-sequence (seq2seq) models to unfold a compact phoneme sequence into acoustic features in the case of TTS [6], [7] or to handle the misalignment of acoustic sequences in the case of VC [8], [9], [10]. A neural vocoder, which generates waveforms sample-by-sample [11], [12], [13], is also a staple of many high-quality speech-generation recipes [6], [14]. Generally speaking, the performance of deep learning approaches is high when training on a large amount of data. For speech generation models, this means that we need many hours of speech from a target speaker to train a model. This limits the ability to scale the technology to many different voices.

Besides improving the naturalness, cloning new voices with a small amount of data is also an active research topic. While there are many different approaches proposed to tackle this problem, they all share the same fundamental principle which is using an abundant corpus to compensate for the lack of data of a target speaker [15]. For neural TTS, we can fine-tune all or part of a well-trained acoustic model using transcribed speech from a target speaker [16]. For neural VC, we can pool the speech data of multiple source and target speakers and share knowledge learned from each [17]. In most of these cases, the data used for training or adaptation is either paired or labeled. However, as all acoustic characteristics of a speaker are fully contained within speech signals, we should hypothetically be able to clone voices by using untranscribed speech only, and this would greatly reduce the cost of building speech generation systems. Disentangling speaker characteristics from linguistic information and representing it as a speaker vector is hence a popular way for cloning voices [18]. Another approach is to use labels auto-generated by speaker-independent automatic speech recognition (ASR) trained on large-scale multi-speaker corpora [19]. Either way, the cloning method is usually formulated for a specific data scenario of a specific speech generation system (either TTS or VC), while a true data-efficient method should work on extremely limited data and also abundant data with or without labels.

From the perspective of voice cloning, TTS and VC can be seen as similar systems that use different inputs for generating speech with a target voice. They share almost the same objective as well as many functional components, but they are normally treated as different systems and are modeled using vastly different frameworks. Several works have used this similarity to combine these two systems into one [19], [20]. However in the end, these works only focus on using one to improve the other [21], [10], [22].

In this work we present our new speech synthesis system, NAUTILUS, which can act as TTS or VC with state-of-the-art (SOTA) quality and highly consistent similarity[1]. More importantly, this combination is not for convenience but to open up the ability to clone unseen voices with a versatile cloning strategy that could be adjusted to the data situation of target speakers. Given this versatility, we show that our system can handle unique speaker characteristics such as L2 accents.

This paper is structured as follows: Section II reviews works on text-to-speech and voice conversion in the context of cloning voices. Section III explains the principles of our framework. Section IV gives details on the proposed NAUTILUS system used in this paper. Section V presents experiment

1 The basic of the voice cloning method for TTS was proposed in [23] and as a proof-of-concept it was also shown that the same principle is applicable for VC in [20]. This new work builds upon the methodology and presents a SOTA unified voice cloning system for TTS and VC.

NAUTILUS: a Versatile Voice Cloning System

Hieu-Thi Luong, Student Member, IEEE, Junichi Yamagishi, Senior Member, IEEE
scenarios and their evaluations. We conclude our findings in Section VII.

II. RELATED WORK ON VOICE CLONING

A. Definition of voice cloning

The term voice cloning is used to refer to a specific speaker adaptation scenario for TTS with untranscribed speech in several works [18], [24]. However in pop culture, it is loosely used to describe technology that resembles VC. In this paper, we use voice cloning as an umbrella term that indicates any type of system that generates speech imitating the voice of a particular speaker. The main difference between voice cloning and speech synthesis is that the former puts an emphasis on the identity of the target speaker [25], while the latter sometimes disregards this aspect for naturalness [26]. Given this definition, a voice cloning can be a TTS, a VC, or any type of speech synthesis system [4], [5]. The NAUTILUS system is designed to be expandable to other input interfaces. However, we focus on TTS and VC, which are two common speech synthesis tasks, in this work as they play an irreplaceable role in our voice cloning method.

The performance of a voice cloning system is judged on many aspects. As a speech generation system, the naturalness and similarity to target speakers are important [6]. As a computer system, a small memory footprint [15] and fast computing time [18], [27] are desirable for practical reasons. However, the defining property of a voice cloning system compared with generic speech synthesis is its data efficiency as this determines its scalability [28]. While data efficiency can be casually interpreted as using as little data as possible [15], a better voice cloning system should not only work in a situation with extremely limited amount of data but also be able to take advantage of abundant speech data [28] when such data become available regardless of the availability of transcriptions [24].

B. Training voice conversion system for target speaker

The conventional VC approach is text-dependent, i.e., it expects training data to be parallel utterances of source and target speakers [29], [30]. As obtaining these utterances is expensive and labor-intensive work, a parallel VC system has to commonly be built with as little as five minutes of data from a speaker [31]. This is inconvenient and it limits the quality of VC systems in general. Many have worked on methodologies for building VC systems with non-parallel utterances [32]. With HMM models, we can formulate a transformation function to adapt pretrained models using non-parallel speech [33], [34]. With recent deep representation learning approaches, the popular method is training a speaker-disentangled linguistic representation either implicitly or explicitly. For implicit cases, Hsu et al. [35] used variational auto-encoder (VAE), while Kameoka et al. [36] used generative adversarial network (GAN) to train a many-to-many non-parallel VC system. These methods use multi-speaker data, conditional labels, and various kinds of regularization to encourage a model to disentangle linguistic content from speaker characteristics via a self-supervised training process. For explicit cases, Sun et al. [36] used phonetic posteriorgrams (PPG) obtained from an ASR model to train an any-to-one non-parallel VC system. As the ASR model is speaker-independent, a PPG-based VC system can theoretically convert the speech of arbitrary source speakers into a target speaker.

Even though a typical VC system is only trained on speech data, recent works have suggested that using transcriptions of training data or jointly training TTS along with VC can further improve the naturalness of generated samples [19], [10].

C. Adapting text-to-speech system to unseen target

A TTS system is typically trained on dozens of hours of transcribed speech [6], [37]. Due to the high requirement for quantity and quality, a professional voice actor is commonly commissioned to record such data in a controlled environment. This makes the conventional approach ill-fitted for the voice cloning task in which we do not have controls over the target speaker, recording environment, or the amount of data. To build a TTS system for speakers with a limited amount of labeled data, we can adapt pretrained models. The initial model can be trained on the data of a single speaker [38] or data pooled from multiple speakers [39], [40]. This simple fine-tuning produces a high-quality model when the data of target speakers is sufficient (e.g., one hour) [28]. When the data is extremely limited (e.g., one minute), we can restrict the tuning to certain speaker components instead of the entire network to prevent overfitting [40], [41], [28]. In summary, speaker adaptation transfers knowledge learned from the abundant data of one or multiple speakers to reduce the demand on a target.

The costly part of the voice cloning system is the data collecting process, especially the transcription of speech. Theoretically speaking, as speaker characteristics are self-contained within an utterance we should be able to clone voices without using text. One practical approach is obtaining automatically annotated transcriptions using a SOTA ASR system [16]. However ASR-predicted transcriptions contain wrong annotations, which affects the performance of the adaptation. Moreover this approach assumes that a well-trained ASR is obtainable for a target language, which makes it impractical for low-resource languages [26] or performing cross-language adaptation [42], [24]. Given the disentanglement ability of deep learning models, another approach is to train a speaker-adaptive model conditioned on a speaker representation extracted from speech [18], [43]. The speaker representation can be an i-vector [44], d-vector [45], [15], or x-vector [46], which are all byproducts of speaker recognition systems. This approach has a computational advantage in that it does not involve an optimization loop [18]. However, the drawback is its limited scalability; in other words the speaker similarity seems to stop improving when using more than a few seconds of speech [28].

D. TTS as speech-chain component

Even though TTS and ASR, two essential modules of spoken dialog systems, are placed at the two ends of the human-machine communication interface and compliment each other,
historically, they are built independently under different frameworks [1], [47]. Recent end-to-end speech models have reduced the technical difference between TTS and ASR systems and opened up the possibility of integrating them into a single ecosystem. Tjandra et al. [48] developed the Speech Chain model which consists of a TTS and ASR that consume each other’s output as their own inputs. Karita et al. [49] factorized TTS and ASR into encoders and decoders and then jointly trained them all together by putting a constraint on the common latent space. The purpose of these unified systems is combining resources and enabling semi-supervised training.

Similar to the situation with ASR, several works have tried to combine VC with TTS [19], [10] or bootstrapping VC from TTS [20], [22]. Hypothetically speaking, given a perfect ASR system, there is no difference between TTS and VC systems. Specifically, the PPG-based VC system [36] is essentially a TTS model stacked on top of an ASR model. Polyak et al. [21] trained a TTS with target voice by combining any-to-one VC and robot-voice TTS systems [21].

III. VERSATILE VOICE CLONING FRAMEWORK

Our voice cloning system, “NAUTILUS”, is a multimodal neural network, that can be used as a TTS [23] or a VC [20] system. It is not just a combination of conventional TTS and VC systems [19] but a carefully designed system that has the ability to clone unseen voices using either transcribed or untranscribed speech [23]. The core concept is to train a latent linguistic embedding (LLE) for use as a stand-in for text when transcription is difficult to obtain. The architecture of our multimodal system resembles the model proposed by Karita et al. [49]; however, they focus on the performance of ASR system instead of speaker adaptation. While the emphasis on linguistic latent features is similar to the PPG-based VC system proposed by Sun et al. [36], their phonetic representation extractor is trained independently with the VC model while our linguistic latent features are jointly trained with the speech generation model. Given the similarity in techniques, we will compare our system with the PPG-based VC system in the experiments.

A. Training latent linguistic embedding with multimodal neural network

The principle components of the voice cloning framework are presented in Fig. 1. The multimodal neural network is essential for our voice cloning methodology. While the neural vocoder is optional, we included it since it is necessary for generating high-quality speech in most recent setups [6], [14]. The proposed system contains four modules, which are encoders and decoders of either text, x, or speech, y. In combinations of encoders and decoders, the modules can perform four transformations: text-to-speech (TTS), speech-to-speech (STS), speech-to-text (STT), and text-to-text (TTT). Combining these modules into a single system is not just for convenience but serves an important purpose. The speech encoder helps the TTS system adapt with untranscribed speech [23], while the text encoder helps the VC system disentangle speaker from the linguistic representation. The text decoder

is the new addition in this paper. While Karita et al. [49] use a similar combination for speech recognition, we focus on speech generation tasks and the text decoder is used as an auxiliary regularizer only.

Our methodology is designed around the training of a speaker-disentangled LLE, z. The LLE in our setup plays the same role as the PPG proposed for VC [35]. However, the LLE is jointly trained with the speech generation modules and contains linguistic information as a whole (instead of phoneme). There are several ways to train the multimodal neural network. It can be trained stochastically [50], step-by-step [22], or jointly [50], [49]. We proposed two methods for the joint training in our previous work [51]: 1) joint-goal where several losses calculated between an output inferred by each decoder and its ground-truth are combined, and 2) tied-layer, where the distance or distortion between two latent spaces obtained from encoders are constrained to be identical. Using one or the other is enough [51], [23], but as they are complementary, we could use them together:

$$\text{loss_{train}} = \text{loss}_{goal} + \beta \text{loss}_{tie}$$

$$= \text{loss}_{tts} + \alpha_{sts} \text{loss}_{sts} + \alpha_{stt} \text{loss}_{stt} + \beta \text{loss}_{tie}$$

where the loss_{tts} in Equation 1 is a TTS loss defined by the text encoder and speech decoder and is used as the anchor to adjust other hyperparameters. loss_{sts} is an STS loss defined by the speech encoder and speech decoder and we de-emphasize loss_{sts} with a weighting parameter, \alpha_{sts}. loss_{stt} is an STT loss defined by the speech encoder and text decoder. Even though the speech-to-text task is not a target one, its loss is
also included to encourage the latent space to focus more on phonemes (but not entirely). Some other works have shown that an auxiliary phoneme classifier helps in boosting the quality of speech generation systems in general [10]. A TTT loss defined by the text encoder and text decoder, loss\textsubscript{sts}, is not included as we do not think that it helps. The last term loss\textsubscript{tie} is for the tied-layer constraint.

In each training step, we calculate each term of the loss\textsubscript{train} using a transcribed speech sample and then optimize all parameters in a supervised manner. Karita \textit{et al.} [49] used a similar loss to jointly train their system but with one important difference, two separated speech samples, one with its transcription and another without, are used to calculate a single training loss. Specifically, loss\textsubscript{sts}, loss\textsubscript{att}, and loss\textsubscript{tie} are calculated using the transcribed sample, while loss\textsubscript{sts} and loss\textsubscript{att} are calculated on the untranscribed sample. This semi-supervised training strategy was proposed to take advantage of an abundant unlabeled corpus [49]. Our system can also benefit from this semi-supervised strategy, but we only focus on supervised training in this work.

For the tied-layer loss, we calculated the symmetrized Kullback-Leibler divergence between the outputs of the text and speech encoders instead of the asymmetric one [23]:

$$\text{loss}_{tie} = \frac{1}{2} L_{KL}(\text{SEnc}(x), \text{SEnc}(y))$$

$$+ \frac{1}{2} L_{KL}(\text{SEnc}(y), \text{SEnc}(x))$$ (2)

The constraints help obtaining a consistent latent space between the text and speech encoders. Through experiments we found that KL divergence is an effective tied-layer loss [23].

Another important aspect is random sampling at the output of the encoders. Thanks to the noise added by the sampling process of the LLE in the training stage, the text and speech decoders are trained in a denoising fashion. This, in turn, makes the speech decoder robust to unseen samples, which is helpful for speaker adaptation.

### B. Speaker adaptation framework

The multimodal network trained in the previous stage is essentially a multi-speaker TTS/VC system; however our goal is to perform voice cloning for unseen speakers. Next, we describe the cloning protocol for a standard scenario that uses untranscribed speech and the supervised scenario which uses transcribed speech in the following subsections.

1) Cloning voice using untranscribed speech: The core mechanism for unsupervised speaker adaptation is the same as from our prior work [23], [20]; however, the detail of the executions have been updated. The voice cloning stage now contains three steps, which takes the neural vocoder into account.

**Step 1 - Adaptation:** This is essentially our legacy unsupervised adaptation stage [23], in which the speech decoder and neural vocoder are adapted separately. We first remove all speaker components and then fine-tune the remaining parameters of the speech decoder using the following loss:

$$\text{loss}_{adapt} = \text{loss}_{sts} + \beta \text{loss}_{cycle}$$ (3)

The speech distortion loss\textsubscript{sts} by itself is enough for the adaptation [23], but we further add a linguistic cycle consistent term loss\textsubscript{cycle} to try to improve the performance. loss\textsubscript{cycle} is the KL divergence between the distributions of natural speech and reconstructed speech as follows:

$$\text{loss}_{cycle} = \frac{1}{2} L_{KL}(\text{SEnc}(y), \text{SEnc}(\tilde{y}))$$

$$+ \frac{1}{2} L_{KL}(\text{SEnc}(\tilde{y}), \text{SEnc}(y))$$ (4)

Even though both loss\textsubscript{sts} and loss\textsubscript{cycle} try to force the reconstructed features to be close to natural speech, they focus on different aspects; loss\textsubscript{sts} is either $l_1$ or $l_2$ frame-based hard distortion of the acoustic features, while loss\textsubscript{cycle} focuses on
linguistic content with soft divergence. We adapt the neural vocoder in a similar manner using its goal loss:

\[
\text{loss}_{\text{adapt}} = \text{loss}_{\text{voc}}
\]

As a neural vocoder depends on speech only, it can be used in an unsupervised adaptation strategy. This is a simple yet effective approach [14].

**Step 2 - Welding:** Even though fine-tuning the acoustic model and the neural vocoder separately can produce sufficient quality [14], there are still mismatches between the generated features and the natural features used to train the vocoder. For text-to-speech systems, Zhao et al. [53] fine-tuned an acoustic model with the losses propagating from a neural vocoder, while Ping et al. [37] jointly trained them together. For voice conversion, due to the duration mismatch between source and target utterances, Huang et al. proposed that the WaveNet vocoder be fine-tuned by using reconstructed acoustic features of a target speaker [54]. Motivated by them, we deploy a “welding” strategy, illustrated in Fig. 2b that conducts fine-tuning by using the reconstructed features of the target speaker in a similar way to Huang’s approach [54], but, for both the speech decoder and neural vocoder like Ping’s method [37] based on the loss function below:

\[
\text{loss}_{\text{weld}} = \text{loss}_{\text{sts}} + \gamma \text{loss}_{\text{voc}},
\]

where loss_{sts} is included to preserve the acoustic space even after the welding process as the speech decoder is assumed to be autoregressive in the domain.

Two practical tactics are further introduced for this step. 1) mean-value LLE: to let the acoustic model learn fine-grained details, we remove the sampling process from the speech encoder and use the mean value instead. 2) mix-in: as losses propagating from the neural vocoder can overpower the speech decoder [53], we propose a mix-in tactic, inspired by drop-out, to ease this problem. Specifically the output of the speech decoder is randomly mixed with natural frames by a percentage to reduce the amount of losses propagated back.

**Step 3 - Inference:** Even though we use the speech encoder to tune the speech decoder and neural vocoder in the adaptation and welding steps, the text encoder can utilize these tuned modules without any further adjustment in inference (See Fig. 2c) thanks to the consistency between the latent spaces of the text and speech encoders. As our cloning method tunes entire modules, the more data available, the better the performance.

2) Alternative strategy to cloning voices with transcribed speech: The strategy for supervised speaker adaptation using transcribed speech was also refined compared with our previous work [23]. Instead of using exactly the same strategy as those for the above unsupervised strategy, we first tune the speech decoder and text encoder together using the transcribed speech since transcriptions could benefit the TTS system.

**Step 1 - Adaptation (supervised alternative):** The supervised strategy for the adaptation step is illustrated in Fig. 3a. We adapt both the speech decoder and text encoder using the following function.

\[
\text{loss}_{\text{adapt}}^{\prime} = \text{loss}_{\text{sts}} + \alpha \text{loss}_{\text{sts}} + \beta \text{loss}_{\text{tie}}
\]

The optimizing loss is similar to that used in the training stage (Equation 1). We use loss_{sts} and loss_{tie} to maintain the linguistic latent space for VC. The welding and inference steps are the same as the unsupervised strategy.

**IV. DETAILS OF NAUTILUS SYSTEM**

The methodology explained in Sec. III can be applied to any neural architecture from the conventional acoustic model [23] to end-to-end (E2E) model [6]. Next we give the details on our system used in the experiments. It is not a fully E2E system but inspired by the E2E model in various ways.

A. Text-speech multimodal system

Our system is shown in Fig. 4. The text representation \( \mathbf{x} \) is a phoneme sequence and the speech representation \( \mathbf{y} \) is mel-spectrogram.

1) Text encoder: the text encoder transforms a compact phoneme sequence \( \mathbf{x} \) into the LLE sequence \( \mathbf{z} \), which has the same length as the acoustic sequence. Our specifications for the text encoder are illustrated in Fig. 4a. The input phoneme sequence is represented as one-hot vectors. As engineered linguistic features are no longer provided, tenc-linguistic-context is used to learn the linguistic context. This is a direct imitation of Tacotron 2 [6] but with quasi-RNN used in place of the standard RNN to speed up the training. The attention mechanism is essential in a E2E setup to unroll the phoneme sequence; our setup, however, uses an explicit duration/alignment module called “tenc-alignment” in training and inference to have direct control over the generated sample prosody. The coarse linguistic features, then, go through several dilated convolution layers called “tenc-latent-context” to capture the local context and smooth out the coarseness. tenc-latent-context has essentially the same design as the acoustic models used in our prior work [23], which used

3The tenc-alignment could be replaced with attention mechanism for convenience, and this could also potentially improve the quality further [53].
residual, skip connection and filter-gate function (Fig. 4a in [23]) to help the gradient flow:

\[ h_t = \tanh(W^f_t h_{t-1} + c^f_t) \odot \sigma(W^g_t h_{t-1} + c^g_t), \]

where \( h_t \) is the output of the \( l \)-th layer, and \( W^f_t, W^g_t, c^f_t, \) and \( c^g_t \) are the weights and biases for filters and gates. The output of the text encoder consists of the mean and standard deviation of a text-encoded LLE sequence.

2) Speech decoder: the speech decoder takes in an LLE sequence \( z \) to generate a respective acoustic sequence \( y \) with a particular voice. It is essentially a multi-speaker speech synthesis model and there are three components that significantly affect the performance: temporal context capturing [56], autoregressive mechanism [57], [55], and speaker modeling [41]. sdec-context-blk captures LLE temporal context by using time-domain convolution (1dconv) layers, which also contain speaker biases in their filters and gates (Fig. 4b in [23]):

\[ h_t = \tanh(W^f_t h_{t-1} + c^f_t + b^{f,(k)}_l) \]
\[ \odot \sigma(W^g_t h_{t-1} + c^g_t + b^{g,(k)}_l), \]

where \( b^{f,(k)}_l \) and \( b^{g,(k)}_l \) are the speaker biases of \( k \)-th speaker in the training speaker pool. The effective type of speaker component depends on the network structure as well as the acoustic features [41]. We previously found that speaker biases work the best for our setup [23].

An autoregressive mechanism is introduced to improve the overall naturalness. sdec-prenet is responsible for the autoregressive dependency that captures the past outputs using causal layers. This is a direct imitation of the AudioEnc proposed by Tachinaba et al. [27]. The layers in sdec-prenet use the highway function in the same way as [27] as follows:

\[ h^f_t = W^f_t h_{t-1}, \]
\[ h^g_t = \sigma(W^g_t h_{t-1}), \]
\[ h_t = h^f_t \odot h^g_t + h_{t-1} \odot (1 - h^g_t) \]

The linguistic context and the past-state token are fed into more causal layers before being transformed into the acoustic features. The architecture of the speech decoder is shown in Fig. 4b. We use the mean absolute error (MAE) as the loss function for the speech generation goals. In the adaptation stage, speaker biases are removed from the speech decoder.

3) Speech encoder: the speech encoder extracts the LLE \( z \) from a given acoustic sequence \( y \) while stripping unnecessary information (i.e., speaker characteristics). It is similar to an ASR model as the output needs to be independent from training speakers, and the model needs to be generalized to unseen targets. We have no strong preference for speech...
encoder specification and simply use several dilated layers to capture the local context as illustrated in Fig. 4d.

4) Text decoder: the text decoder takes an LLE sequence \( z \) and predicts the phoneme posterior \( \tilde{x} \) at each frame. This is a new component introduced in this work compared with previous ones [23]. Unlike other modules that would be reused in various stages, the shallow text decoder is included in the training only and acts as an auxiliary regularizer. Its purpose is forcing the latent linguistic embedding to focus more on phoneme information, which we found important for generating utterances with clear pronunciation. The balance between phoneme and other linguistic information is adjustable using the joint-goal weight \( \alpha_{stt} \) and the representative power of the text decoder itself. This is why we use a couple of layers only to model the text decoder (Fig. 4c). The cross-entropy criterion is used as the loss function of the phoneme classifier.

B. WaveNet vocoder

An auto-regressive WaveNet model conditioned on a mel-spectrogram [58], [6], [14] is used as the neural vocoder of our setup. WaveNet is trained on either 22.05kHz or 24kHz speech depending on the scenarios. Waveform amplitudes are quantized by using 10-bit \( \mu \)-law. The network consists of 40 dilated causal layers containing speaker biases. Both the residual and skip channels are set at 128. This is a typical setup for WaveNet [11]. In the adaptation stage, speaker biases are removed before fine-tuning.

C. Training, adapting, and inferring configurations

The General American English lexicon [59] was used for text representation, and 56 distinct phonemes were found in our training data. An 80-dimensional mel-spectrogram was used as acoustic representation. The mel-spectrogram was calculated by using a 50-ms window size and 12.5-ms shift size. This was inspired by the setup of E2E TTS model [6], [27]. The weighting parameters of the optimizing losses were \( \alpha = 0.1, \beta = 0.25 \) and \( \gamma = 0.01 \). The learning rate was set at 0.1 for all optimizing stages. The dropout rate was set at 0.2 for most components apart from \( \text{tenc-linguistic-context} \) and \( \text{sdec-prenet} \), for which the rate was set at 0.5. The training was stopped when loss on validation stopped improving for ten consecutive epochs.

One hundred speakers of the VCTK corpus [60] were used to train the multi-speaker text-speech system and the WaveNet vocoder. The sampling rate was converted to the target scenarios. Among the remaining speakers, one male and one female with an American accent were used as targets for an experiment described in Sec. [V-B]. All common sentences were removed from the training so they could be used for evaluation. As VCTK lacks diversity in linguistic content, we first used 24-kHz LibriTTS corpus [61] to warm-up the text-speech network. Only \( \text{train-clean-100} \) and \( \text{train-clean-360} \) sets, which are 245 hours in total, were used to reduce the warming time. The phoneme alignments of each corpus were extracted using an ASR model trained on the same corpus using the KALDI toolkit [62]. For evaluated utterances, the model trained on the LibriTTS corpus is used to extract their phoneme alignments.

There were two voice cloning experiments, scenarios A and B. For the voice cloning stage, the number of epochs was fixed to create a uniform process. Specifically, for scenario A described in Sec. [IV-D], we first adapted the text-speech model for 256 epochs, the vocoder for 128 epochs, and then welded them together for 64 more. For scenario B described in Sec. [V-B], the number of epochs was 256, 64, and 32, respectively. The \textit{mix-in} rate in the welding step was set at 0.9.

For the inference stage, the speech encoder used its mean output for VC while text encoder sampled a LLE sequence from Gaussian distributions for TTS as shown in Fig. 2c. To maintain stochasticity but reduce the chance of sampling undesirable outliers, we multiplied the standard deviation output of the text encoder by 0.1 before random sampling.

D. Evaluation measurements

In this work, we treat our system as a whole, instead of focusing on individual techniques, and we compare it with other third-party systems. For objective evaluation, we used an ASR model\(^4\) to calculate the word error rate (WER) of generated speech. Note that the WER was only used as a reference point since it is highly sensitive to the training data of the ASR model. For subjective evaluation, we used MOS in a 5-point scale for quality and DMOS on a 4-point scale for speaker similarity [51]. In most questions on speaker similarity, participants were asked to compare speaker similarity of a generated utterance with a natural utterance. However, scenario A included additional questions for comparing speaker similarity between generated utterances. In scenario B, the participants were also asked to do several AB tests on quality and speaker similarity. In the AB test, two speech samples were shown at each test page and participants were asked to choose the better of the two. These questions were used to highlight the fine-grained differences between generation systems. Each participant in our subjective listening tests was asked to do ten sessions.

V. Experiment scenarios and evaluations

As our system can clone voices by using either transcribed or untranscribed speech and can be used as a TTS or VC system, it would be difficult to evaluate all of these tasks in a single experiment. Therefore, we tested its performance and versatility under two separate scenarios. The first scenario focuses more on VC and cloning voices with untranscribed speech, while the second scenario focuses more on TTS

\(^4\)A chain system based on TDNN-F pretrained on the Librispeech corpus [63] was used for calculation (http://kaldi-asr.org/models/m13).
TABLE II

| System  | VCC2TF1 | Target speakers (%WER) | VCC2TF2 | Target speakers (%WER) | VCC2TM1 | Target speakers (%WER) | VCC2TM2 |
|---------|---------|------------------------|---------|------------------------|---------|------------------------|---------|
| XV  | 5.25    | 2.98                   | 4.86    | 2.60                   | 18.57   | 2.65                   | 18.27   |
| N10  | 7.21    | 7.99                   | 11.79   | 9.99                   | 7.21    | 7.99                   | 11.79   |
| N10×  | 9.62    | 11.52                  | 8.67    | 9.21                   | 9.62    | 11.52                  | 8.67    |
| N13×  | 23.31   | 21.68                  | 31.57   | 27.37                  | 23.31   | 21.68                  | 31.57   |
| N13  | 32.25   | 24.80                  | 21.41   | 26.96                  | 32.25   | 24.80                  | 21.41   |
| N17×  | 25.47   | 34.44                  | 35.23   | 25.88                  | 25.47   | 34.44                  | 35.23   |
| N17  | 38.08   | 31.44                  | 35.23   | 25.88                  | 38.08   | 31.44                  | 35.23   |
| VCA  | 25.34   | 26.02                  | 27.37   | 25.75                  | 25.34   | 26.02                  | 27.37   |
| VCA×  | 30.62   | 27.51                  | 23.71   | 22.63                  | 30.62   | 27.51                  | 23.71   |
| TTSu  | 7.72    | 8.40                   | 6.23    | 7.18                   | 7.72    | 8.40                   | 6.23    |

Source speakers (%WER)

| System  | VCC2SF3 | Source speakers (%WER) | VCC2SF4 | Source speakers (%WER) | VCC2SM3 | Source speakers (%WER) | VCC2SM4 |
|---------|---------|------------------------|---------|------------------------|---------|------------------------|---------|
| S00  | 5.69    | 4.88                   | 5.69    | 3.22                   | 5.69    | 4.88                   | 5.69    |

and performance of the supervised and unsupervised speaker adaptation strategies.

A. Cloning voices using untranscribed speech

In the first scenario, scenario A, we tested the ability to clone voices by using a small amount of untranscribed speech (about five minutes). A system showing good performance under this scenario is expected to have the capability to clone thousands of voices efficiently and cheaply.

1) Description of scenario A: we re-enacted the SPOKE task of Voice Conversion Challenge 2018 (VCC2018) [31] for this scenario. The original goal of the task was to build VC systems for 4 target English speakers (2 males and 2 females) using 81 utterances (Table I). These systems were used to convert the speech of 4 source speakers (2 males and 2 females) into each of the target voices. We followed the VCC2018 guideline [31] faithfully with one extension – we evaluated TTS systems as well as VC systems at the same time. These TTS systems were required to train on the untranscribed speech of the target speakers. In the inference stage, transcriptions of source utterances were used to generate speech with TTS systems. As there were only 35 unique sentences, we generated each sentence twice. In summary, each TTS system produced 70 utterances for each target speaker while each VC system produced 140 utterance. We split each VC system into two entities, one for same-gender conversion denoted by the superscript “=” and the other for cross-gender denoted by “×”.

2) Systems: We evaluated the following TTS and VC systems in scenario A:

- **XV**: a speaker-adaptive E2E TTS system using the x-vector [18], [15], [46]. XV was used as a third-party unsupervised TTS baseline. We used the libritts_tacotron2.v1 model and the speaker-independent WaveNet vocoder libritts.wavenet.mol.v1 which were trained on the LibriTTS corpus to realize this approach. Both are available at the ESPnet repository [6] as X vectors. As the x-vector is utterance-based, we randomly picked five utterances (about ten seconds) from the training pool of target speakers to extract the x-vector each time we generate an utterance.
- **N10**: the winner of the VCC2018 SPOKE task. N10 contains a PPG-based acoustic model [36] and a fine-tuned WaveNet vocoder [14]. It uses a speaker-independent ASR model trained on hundreds of hours of labeled data to extract PPG from speech. N10 clones voice without using the speech data of source speakers.
- **N13, N17 (NR)**: the runners up of the VCC2018 SPOKE task in terms of quality and similarity, respectively. To reduce the amount of systems, we treat them as one (denotes as NR) and use N13 in the quality evaluation while using N17 [65] in the similarity evaluation.
- **VCA**: our unsupervised VC system follows the adaptation process described in Sec. III-B1. The letter “A” as in “any-to-one” indicates that the model is not trained on source speakers. The word unsupervised means that the cloning is performed with untranscribed speech in the context of our current work. It is operated at 22.05 kHz to be compatible with the target speakers.
- **TTSu**: our unsupervised TTS system. As we did not train an automatic duration model, we used the duration extracted from the same-gender source speakers to generate speech from text. This means that TTSu shares the same duration model as VCAu (and other same-gender VC systems). This reduces the difference in experimental conditions between them and allows us to make more insightful observations.
- **T00 and S00**: natural utterances of the target and source speakers used as references, respectively.

3) Evaluation: twenty-eight native English speakers participated in our subjective test for scenario A. Listeners were asked to answer 18 quality and 22 similarity questions in each session. In summary, each system was judged 560 times for each measurement, while natural speech systems (T00 and S00) were judged 280 times. The objective and subjective evaluation results are shown in Table II and Fig. 5 with many interesting observations. a) XV had better quality but worse
similarity than the runners up of VCC2018. It also had the lowest WER; one reason is it trained on LibriTTS a subset of Librispeech. b) Our systems had high scores in both subjective measurements. Interestingly our TTS system has lower WER than our VC systems. c) Even though we had a lower score for quality than did N10, the similarity seem to be higher. d) Our TTS and VC systems had highly consistent results, while there was a gap between the same-gender and cross-gender N10 subsystems. This was perpetuated by extra similarity evaluations between the generated systems presented in Fig. 5. The similarity between our TTSu and VCAu systems was higher than the similarity between TTSu and N10.

4) Scenario conclusion: Even though the naturalness of our voice cloning system was slightly worse than N10 (again the best system at VCC2018), generally speaking it has achieved performance that is comparable to SOTA systems considering the difference in experimental conditions (e.g., the amount of data used in the training stage). More importantly, our system can seamlessly switch between TTS and VC modes with high consistency in terms of speaker characteristics. This is a desirable trait that would be useful for many applications.

| Speaker | Database | Gender | Accent/L1 | Quantity | Duration |
|---------|----------|--------|-----------|----------|----------|
| p299 VCTK | female | American | 325 utt. | 11.2 min |
| p345 VCTK | male | American | 325 utt. | 11.0 min |
| MF6 EMIME | female | Mandarin | 145 utt. | 10.2 min |
| MM6 EMIME | male | Mandarin | 145 utt. | 11.3 min |

B. Capturing unique speaker characteristics

As mentioned earlier, the way voice cloning is differentiated from speech synthesis is that it should prioritize utilize the unique characteristics of target speakers. While it is easy for listeners to grasp general global characteristics (e.g., average pitch), it is more difficult to notice local subtle traits (e.g., pronunciation of particular words) with just a single reference utterance. We could use famous individuals as targets [25], but this assumes that listeners would be familiar with them. In scenario B, we therefore used non-native speakers as targets to highlight their unique characteristics. This is convenient for subjective evaluation as native speakers can generally spot their distinctiveness without any explanation about the linguistic aspect of it [66]. In simple words, the goal of scenario B was to reproduce the accent of non-native speakers. This scenario is closely related to reducing accents [67], [68] or controlling accents [24] tasks.

1) Scenario description: the target speakers for this scenario included two American and two non-native English speakers who use Mandarin as their native language. Each speaker had about 10 minutes of speech as listed in Table III. As the base model was trained with native speakers of English, the speakers from the VCTK corpus represented the standard easy task while the speakers from the EMIME corpus [69] represented difficult and unique target speakers. The evaluated systems were required to be built with either the transcribed or untranscribed speech of the targets. Twenty common sentences from the VCTK corpus were used for the evaluations. Each sentence was generated twice by each TTS system, which totaled 40 utterances. In the case of VC, one female (p299) and one male (p311) with a general American accent included in the training pool are used as source speakers.

2) Systems: The following TTS and VC systems were used for the evaluation in scenario B:

- **XV**: the same x-vector system in scenario A is reused as the unsupervised baseline of TTS.
- **FT**: a fine-tuned E2E TTS system was used as the supervised baseline. We used ljspeech.tacotron2.v3, implemented with ESPNet [20], as the initial model. It was trained with 24 hours of the transcribed speech of a female speaker from the LJSpeech corpus [71]. An initial WaveNet vocoder was also trained with the same corpus. When cloning voices, we fine-tuned both acoustic and vocoder models with the transcribed speech of the targets. This system represented a simple supervised approach by fine-tuning a well-trained single speaker model [16].
- **VCM**: our unsupervised VC system followed the adaptation process described in Sec. III-B1 using untranscribed speech. The letter “M” as in “many-to-one” indicates that the source speakers were included in the training pool of the base model. The system was operated in 24kHz.
- **VCM**: our supervised VC system followed the cloning process described in Sec. III-B2 using transcribed speech. The supervised strategy is more relevant to TTS, but we still included its VC counterpart.
- **TTS**: our unsupervised TTS system. The duration is extracted from the source speakers of VC. This means our TTS and VC systems share the same duration model.
- **TTS**: our supervised TTS system using the alternative supervised adaptation strategy.
- **NAT**: the natural utterances of the target speakers.

3) Evaluation: Thirty-two native speakers took part in our subjective evaluation for scenario B. As the participants were native English speakers living in Japan and many work as English teachers, we expected that they could quickly pick up on the non-native accents. Each session had 18 quality and 18 similarity questions that contain utterances of both native and non-native speakers. Besides the standard MOS tests, we also included several AB tests in this scenario. In summary, each system was evaluated 640 times for each assessment. The objective evaluation result are listed in Table III and the

### Table III

| Speaker | Database | Gender | Accent/L1 | Quantity | Duration |
|---------|----------|--------|-----------|----------|----------|
| p299 VCTK | female | American | 325 utt. | 11.2 min |
| p345 VCTK | male | American | 325 utt. | 11.0 min |
| MF6 EMIME | female | Mandarin | 145 utt. | 10.2 min |
| MM6 EMIME | male | Mandarin | 145 utt. | 11.3 min |

### Table IV

| System | VCTK-p294 | VCTK-p345 | EMIME-MM6 | EMIME-MM6 |
|--------|----------|----------|-----------|-----------|
| NAT* | 6.09 | 8.09 | 36.24 | 43.37 |
| XV | 3.50 | 24.05 | 3.33 | 3.31 |
| FT | 13.39 | 20.09 | 57.53 | 42.01 |
| VCM | 22.22 | 24.05 | 27.70 | 27.09 |
| TTS | 9.28 | 10.05 | 36.38 | 38.20 |
| Source speakers (%WER) | - | - | - | - |

*calculated on all training utterances of source speakers.
**calculated on natural utterances of source speakers.
subjective evaluation results are shown in Fig. 6. Here the results of native and non-native speakers are separately shown.

For the standard case with native target speakers, the subjective results show high MOS scores for most systems as shown in Fig. 6a. The new results here are comparisons between supervised and unsupervised approaches. Comparing the XV and FT systems, which represent unsupervised and supervised TTS baselines, we see that the fine-tuned one was significantly better than the speaker embedding one as it benefited from all ten minutes of data. Similar to scenario A, XV system has better WER than FT for many targets. Among our systems, the difference between the supervised and unsupervised strategies was marginal, but they were all better than the supervised baseline FT. One hypothesis is that our approaches are less sensitive to overfitting thanks to the multi-speaker corpus, speaker factorization and denoising training while FT has a higher possibility of overfitting when using ten minutes of speech \[16\], \[22\]. These observations are also supported by AB-preference tests (See the bottom part of Fig. 6a).

For the challenging case with non-native target speakers, the subjective results revealed more interesting tendencies as shown in Fig. 6b. This scenario not only revealed the robustness of the voice cloning methods but also the listeners’ behaviors. First, we can see that our systems had higher similarity scores than the TTS baselines, FT and XV. The differences between our supervised and unsupervised strategies was more profound in the non-native cases. TTS\_s seemed to have higher similarity than TTS\_u. Next, interestingly we see that the natural speech of the non-native speakers (NAT) had lower quality scores than its native counterpart. This would be because our native listeners perceived the “quality” of speech with strong non-native accents as low. As a result, the quality and similarity measurement in this case was no more a positive correlation. The average per-listener results for non-native NAT are plotted in Fig. 6c. Even a negative correlation was found for the subjective results of the TTS baselines, FT and XV, indicating that higher-quality speech corresponded to less accented speech and hence lower speaker similarity to non-native target speakers. This highlights the pros and cons of these adaptation methods. The WER of the non-native natural speech (NAT) was significantly worse than the native speakers as expected, while TTS\_s is worse than TTS\_u.

In summary, the proposed system had higher speaker similarity than the baseline systems. Our TTS system, in particular, benefited from the supervised strategy although the improvement was relatively small. Regarding the TTS\_s and the other two VC systems that had slightly better quality than the natural speech, we suspect that this is due to the reduced/lack of accents of their generated speech. This hints at potential uses for other accent-related tasks \[67\].

4) Scenario conclusion: The subjective results have shown that the fine-tuning approach is better at capturing unique speaker characteristics than the speaker embedding approach when data are sufficient. Our systems, in particular, achieved high performance for native speakers as well as non-native speakers. Moreover our cloning strategy can be adjusted to take advantage of the transcriptions if they are available. In the meantime, the experiment also points out the limitations of the subjective evaluation. While the current quality and similarity questions work well for native speakers, listeners’ judgements were biased when they needed to evaluate the voices of non-native speakers.

VI. CONCLUSION

In this paper, we showed that our voice cloning system, “NAUTILUS”, can achieve state-of-the-art performance. More importantly, it can act as a text-to-speech or voice conversion system with high consistency in terms of speaker characteristics when switching between the two. With the versatile cloning strategy, which can be adjusted to specific data situation of a target speaker, it is potentially useful for many other interesting tasks like accent reduction \[67\] or cross-lingual voice cloning \[72\], \[73\]. For future work, we will focus on evaluating our systems by using different architectures for text-speech systems \[7\], \[22\] or neural vocoders \[74\], \[13\] to solve specific voice cloning scenarios \[24\], \[20\]. Finally given the multimodal structure, extending our system to other speech generation tasks (e.g., video-to-speech \[3\]) would be a natural direction toward a unified voice cloning framework.
ACKNOWLEDGMENTS

This work was partially supported by a JST CREST Grant (JPMJCR18A6, VoicePersonae project), Japan, and MEXT KAKENHI Grants (16H06302, 17H04687, 18H04120, 18H04112, 18KT0051), Japan.

REFERENCES

[1] K. Tokuda, T. Yoshimura, T. Masuko, T. Kobayashi, and T. Kitamura, “Speech parameter generation algorithm,” in Proc. ICASSP, 2001, pp. 1315–1318.
[2] A. Kain and M. W. Macon, “Spectral voice conversion for text-to-speech synthesis,” in Proc. ICASSP, 1998, pp. 285–288.
[3] T. L. Cornu and B. Milner, “Reconstructing intelligible audio speech from visual speech features,” in Proc. INTERSPEECH, 2015, pp. 3355–3359.
[4] D. Michelsanti, O. Slizovskaia, G. Haro, E. Gómez, Z.-H. Tan, and J. Jensen, “Vocoder-based speech synthesis from silent videos,” arXiv preprint arXiv:2004.02541, 2020.
[5] G. Krishna, C. Tran, Y. Han, and M. Carnahan, “Speech synthesis using eeg,” in Proc. ICASSP, 2020, pp. 1235–1238.
[6] J. Shen, R. Pang, R. J. Weiss, M. Schuster, N. Jaitly, Z. Yang, Z. Chen, Y. Zhang, Y. Wang, R. Skerry-Ryan, R. A. Saurous, Y. Agiomyrgianakis, and Y. Wu, “Natural TTS synthesis by conditioning WaveNet on Mel spectrogram predictions,” in Proc. ICASSP, 2018, pp. 4779–4783.
[7] N. Li, S. Liu, Y. Liu, S. Zhao, and M. Liu, “Neural speech synthesis with transformer network,” in Proc. AAAI Conf. AI, vol. 33, 2019, pp. 6706–6713.
[8] H. Miyachi, Y. Saito, S. Takamichi, and H. Saruwatari, “Voice conversion using sequence-to-sequence learning of context posterior probabilities,” Proc. INTERSPEECH, pp. 1268–1272, 2017.
[9] K. Tanaka, H. Kameoka, T. Kaneko, and N. Hojo, “Att2seq-vc: Sequence-to-sequence voice conversion with attention and context preservation mechanisms,” in Proc. ICASSP, 2019, pp. 6805–6809.
[10] J. Zhang, Z. Liu, and L.-R. Dai, “Non-parallel sequence-to-sequence voice conversion with disentangled linguistic and speaker representations,” IEEE/ACM Trans. Audio, Speech, Language Process, vol. 28, 2020, pp. 540–552, 2019.
[11] A. van den 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.
[12] R. Prenger, R. Valle, and B. Catanzaro, “Waveglow: A flow-based generative model for raw audio,” arXiv preprint arXiv:1906.07414, 2019.
[13] Y. Zhang, R. J. Weiss, H. Zen, Y. Wu, Z. Chen, R. Skerry-Ryan, Y. Jia, A. Rosenberg, and B. Ramabhadran, “Learning to speak fluently in a foreign language: Multilingual speech synthesis and cross-language voice cloning,” Proc. INTERSPEECH, pp. 2080–2084, 2019.
[14] J. Lorenzo-Trueba, F. Fang, X. Wang, I. Echizen, J. Yamagishi, and T. Kinnunen, “Can we steal your vocal identity from the internet?: Initial investigation of cloning obamas voice using gan, wavelet and low-quality found data,” in Proc. Odyssey, 2018, pp. 240–247.
[15] A. Gutkin, L. Ha, M. Jansche, K. Pipatrisitawat, and R. Sprosi, “Ts for low-resource languages: A bangla synthesizer,” in Proc. LREC, 2016, pp. 2005–2010.
[16] H. Tachibana, K. Uenoyma, and S. Aihara, “Efficiently trainable text-to-speech system based on deep convolutional networks with guided attention,” in Proc. ICASSP, 2018, pp. 4784–4788.
[17] Y. Chen, Y. Assael, B. Shillingford, D. Budden, S. Reed, H. Zen, Q. Wang, L. C. Cobo, A. Trask, B. Laurie, C. Gulcehre, A. van den Oord, O. Vinyals, and N. de Freitas, “Sample efficient adaptive text-to-speech,” arXiv preprint arXiv:1809.10460, 2018.
[18] Y. Stylianou, O. Cappe, and E. Moulines, “Statistical methods for voice quality transformation,” in Proc. EUROspeech, 1995, pp. 447–450.
[19] T. Toda, A. W. Black, and K. Tokuda, “Voice conversion based on maximum-likelihood estimation of spectral parameter trajectory,” IEEE Trans. Audio, Speech, Language Process., vol. 15, no. 8, pp. 2222–2235, 2007.
[20] J. Lorenzo-Trueba, J. Yamagishi, T. Toda, D. Saito, F. Villavicencio, T. Kinnunen, and Z. Ling, “The voice conversion challenge 2018: Promoting development of parallel and nonparallel methods,” in Proc. Odyssey, 2018, pp. 195–202.
[21] H. Kameoka, T. Kaneko, K. Tanaka, and N. Hojo, “Stargan-vc: Non-parallel many-to-many voice conversion using star generative adversarial networks,” in Proc. SLT, 2018, pp. 266–273.
[22] Y. Chen, M. Chu, E. Chang, J. Liu, and R. Liu, “Voice conversion with smoothed gm and map adaptation,” in Proc. EUROspeech, 2003, pp. 2413–2416.
[23] T. Toda, Y. Ohtani, and K. Shikano, “Eigenvoice conversion based on gaussian mixture model,” in Proc. INTERSPEECH, 2006, pp. 2446–2449.
[24] C.-C. Hsu, H.-T. Hwang, Y.-C. Wu, Y. Tsao, and H.-M. Wang, “Voice conversion from non-parallel corpora using variational auto-encoder,” in Proc. APSIPA, 2016, pp. 1–6.
[25] L. Sun, K. Li, H. Wang, S. Kang, and H. Meng, “Phonetic posterior-grams for many-to-one voice conversion without parallel data training,” in Proc. ICME, 2016, pp. 1–6.
[26] W. Ping, K. Peng, and J. Chen, “Clarinet: Parallel wave generation in end-to-end text-to-speech,” in Proc. ICLR, 2019, pp. 1–15.
[27] Z. Huang, H. Li, M. Lei, and Z. Yan, “Linear networks based speaker adaptation for DNN-based TTS synthesis using hsmm-based speaker adaptation and adaptive training,” IEICE T. Inf. Syst., vol. 90, no. 2, pp. 533–543, 2007.
[28] Y. Fan, Y. Qian, F. K. Soong, and L. He, “Multi-speaker modeling and speaker adaptation for DNN-based TTS synthesis,” in Proc. ICASSP, 2015, pp. 4475–4479.
[29] H.-T. Luong and J. Yamagishi, “Scaling and bias codes for modeling speaker-adaptive DNN-based speech synthesis systems,” in Proc. SLT, 2018, pp. 610–617.
[30] Y.-N. Chen, Y. Jiao, Y. Qian, and F. K. Soong, “State mapping for cross-language speaker adaptation in tts,” in Proc. ICASSP, 2009, pp. 431–434.
[31] S. Takaki, Y. Nishimura, and J. Yamagishi, “Unsupervised speaker adaptation for DNN-based speech synthesis using input codes,” in Proc. APSIPA, 2018, pp. 649–658.
[32] Z. Wu, P. Swietojanski, C. Veaux, S. Renals, and S. King, “A study of speaker adaptation for DNN-based speech synthesis,” in Proc. INTERSPEECH, 2015, pp. 877–881.
[33] R. Doddipatla, N. Braunschweiler, and R. Maia, “Speaker adaptation in DNN-based speech synthesis using d-vectors,” in Proc. INTERSPEECH, 2017, pp. 3404–3408.
[34] E. Cooper, C.-L. Lai, Y. Yasuda, F. Fang, X. Wang, N. Chen, and J. Yamagishi, “Zero-shot multi-speaker text-to-speech with state-of-the-art neural speaker embeddings,” arXiv preprint arXiv:1910.10838, 2019.
[35] M. Gales, S. Young et al., “The application of hidden markov models in speech recognition,” Foundations and Trends® in Signal Processing, vol. 1, no. 3, pp. 195–304, 2008.

[11] J. Zhang, Z. Liu, and L.-R. Dai, “Wavenet: A generative model for raw audio,” arXiv preprint arXiv:1609.03499, 2016.
A. Tjandra, S. Sakti, and S. Nakamura, “Listening while speaking: Speech chain by deep learning,” in Proc. ASRU, 2017, pp. 301–308.

S. Karita, S. Watanabe, T. Iwata, M. Delcroix, A. Ogawa, and T. Nakatani, “Semi-supervised end-to-end speech recognition using text-to-speech and autoencoders,” in Proc. ICASSP, 2019, pp. 6166–6170.

B. Li and H. Zen, “Multi-language multi-speaker acoustic modeling for lstm-rnn based statistical parametric speech synthesis,” in Proc. INTERSPEECH, 2016, pp. 2468–2472.

H.-T. Luong and J. Yamagishi, “Multimodal speech synthesis architecture for unsupervised speaker adaptation,” in Proc. INTERSPEECH, 2018, pp. 2494–2498.

A. B. L. Larsen, S. K. Sønderby, H. Larochelle, and O. Winther, “Autoencoding beyond pixels using a learned similarity metric,” arXiv preprint arXiv:1512.09300, 2015.

Y. Zhao, S. Takaki, H.-T. Luong, J. Yamagishi, D. Saito, and N. Mienatsu, “Wasserstein gan and waveform loss based acoustic model training for multi-speaker text-to-speech synthesis systems using a wavenet vocoder,” IEEE Access, vol. 6, pp. 60478–60488, 2018.

W.-C. Huang, Y.-C. Wu, H.-T. Hwang, P. L. Tobing, T. Hayashi, K. Kobayashi, T. Toda, Y. Tsao, and H.-M. Wang, “Refined wavenet vocoder for variational autoencoder based voice conversion,” in Proc. EUSIPCO, 2019, pp. 1–5.

O. Watts, G. E. Henter, J. Fong, and C. Valentini-Botinhao, “Where do the improvements come from in sequence-to-sequence neural tts?” in Proc. SW 10th, 2019.

H. Zen and H. Sak, “Unidirectional long short-term memory recurrent neural network with recurrent output layer for low-latency speech synthesis,” in Proc. ICASSP, 2015, pp. 4470–4474.

X. Wang, S. Takaki, and J. Yamagishi, “An autoregressive recurrent mixture density network for parametric speech synthesis,” in Proc. ICASSP, 2017, pp. 4895–4899.

T. Hayashi, A. Tamamori, K. Kobayashi, K. Takeda, and T. Toda, “An investigation of multi-speaker training for wavenet vocoder,” in Proc. ASRU, 2017, pp. 712–718.

K. Richardson, R. A. Clark, and S. Fitt, “Robust Its rules with the combelix speech technology lexicon,” in Proc. INTERSPEECH, 2009.

C. Veaux, J. Yamagishi, and K. MacDonald, “CSTR VCTK corpus: English multi-speaker corpus for CSTR voice cloning toolkit.” 2017, http://dx.doi.org/10.7488/ds/1994.

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, pp. 1526–1530.

D. Povey, A. Ghoshal, G. Boulianne, L. Burget, O. Glembek, N. Goel, M. Hannemann, P. Motlicek, Y. Qian, P. Schwarz, J. Silovsky, G. Stemmer, and K. Vesely, “The kaldi speech recognition toolkit,” in Proc. ASRU, 2011.

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

S. Watanabe, T. Hori, S. Karita, T. Hayashi, J. Nishitoba, Y. Unno, N. S. Aryal and R. Gutierrez-Osuna, “Can voice conversion be used to reduce non-native accents?” in Proc. INTERSPEECH, 2010.

Y. Oshima, S. Takamichi, T. Toda, G. Neubig, S. Sakti, and S. Nakamura, “Non-native text-to-speech preserving speaker individuality based on partial correction of prosodic and phonetic characteristics,” IEICE Trans. Inf. & Syst., vol. 99, no. 12, pp. 3132–3139, 2016.

M. Wester and H. Liang, “The EMIME mandarin bilingual database,” 2011, http://hdl.handle.net/1842/4862.

T. Hayashi, R. Yamamoto, K. Inoue, T. Yoshimura, S. Watanabe, T. Toda, K. Takeda, Y. Zhang, and X. Tan, “Esnpnet-tts: Unified, reproducible, and integratable open source end-to-end text-to-speech toolkit,” in Proc. ICASSP, 2020, pp. 7654–7658.

K. Ito, “The LJ speech dataset,” 2017, https://keithito.com/LJ-Speech-Dataset/.

M. Abe, K. Shikano, and H. Kuwabara, “Statistical analysis of bilingual speakers speech for cross-language voice conversion,” J. Acoust. Soc. Am., vol. 90, no. 1, pp. 76–82, 1991.

Y. Zhou, X. Tian, H. Xu, R. K. Das, and H. Li, “Cross-lingual voice conversion with bilingual phonetic posteriorgram and average modeling,” in Proc. ICASSP, 2019, pp. 6790–6794.

S. Mehri, K. Kumar, I. Gulrajani, R. Kumar, S. Jain, J. Sotelo, A. Courville, and Y. Bengio, “Samplerlm: An unconditional end-to-end neural audio generation model,” arXiv preprint arXiv:1612.07837, 2016.