Controllable Accented Text-to-Speech Synthesis

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Abstract—Accented text-to-speech (TTS) synthesis seeks to generate speech with an accent (L2) as a variant of the standard version (L1). Accented TTS synthesis is challenging as L2 is different from L1 in both in terms of phonetic rendering and prosody pattern. Furthermore, there is no easy solution to the control of the accent intensity in an utterance. In this work, we propose a neural TTS architecture, that allows us to control the accent and its intensity during inference. This is achieved through three novel mechanisms, 1) an accent variance adaptor to model the complex accent variance with three prosody controlling factors, namely pitch, energy and duration; 2) an accent intensity modeling strategy to quantify the accent intensity; 3) a consistency constraint module to encourage the TTS system to render the expected accent intensity at a fine level. Experiments show that the proposed system attains superior performance to the baseline models in terms of accent rendering and intensity control. To our best knowledge, this is the first study of accented TTS synthesis with explicit intensity control.

Index Terms—Text-to-speech (TTS) synthesis, Controllable, Accent, Accent intensity

I. INTRODUCTION

ACCENTED text-to-speech (TTS) synthesis aims to synthesize speech with foreign accent instead of native speech. In other words, it seeks to generate speech with an accent (L2) as a variant of the standard version (L1). Recently, much progress has been made in the quality of neural TTS synthesis for L1 speech [1], [2], for example, WaveNet [3], Deep-Voice 1, 2, 3 [4]–[6], Char2Wav [7], Tacotron 1, 2 [8], [9], Transformer-TTS [10] and FastSpeech1 [11]. Neural TTS has outperformed conventional concatenative and statistical parametric approaches, where neural vocoders play an important role [12]–[15]. Accent is characterized by a distinctive manner of expression that is influenced by the mother tongue, social group of speakers, or spoken in a particular region [16]. Generally, people find it easier to speak with others within their own accent group. Therefore, the wide adoption of speech applications, such as chatbot and movie dubbing, calls for the study of accented TTS synthesis.

Phoneme substitution and accent variance are two key aspects in accent rendering [16], [17]. Phoneme substitution refers to the situation where L2 speakers pronounce L1 phonemes differently [18]. On the other hand, L2 speakers exhibit complex prosody in terms of pitch, energy, and duration [19], that is referred to as accent variance. This paper is focused on the study of accent variance.

An L2-accented TTS system is expected to produce human-like natural speech, just like any TTS system, at the same time to generate speech with an intended accent at an appropriate intensity [19]. The state-of-the-art neural TTS systems typically are trained for a standard voice. It remains a challenge how to effectively control the prosody of accent when rendering speech. We identify two challenges when dealing with accent variance.

First, inadequate modeling of accent variance often leads to a flat L2 speech without noticeable accent signature. Note that an L2 speech is highly expressive particularly in prosody, such as pitch, energy and rhythm. In the statistical approach to TTS, such as hidden Markov model (HMM), there have been attempts to address this problem [20], [21]. In the neural TTS approach, FastSpeech2 [1], FastPitch [22], Meta-StyleSpeech [23], and DAFT-EXPRT [24], pitch and energy predictors are studied. It remains as a challenge how we model the accent variance effectively with interpretable prosodic attributes such as pitch, energy, and duration. To this end, we study a novel neural approach to model the accent variance.

Second, it is difficult to control the intensity of accent because of the lack of well-defined intensity descriptors. In the HMM-based TTS framework, Wutiwiwatchai et al. [25] proposed an accent level adjustment mechanism for bilingual TTS synthesis, where the accent level is adjusted by means of interpolation between HMMs of native phones and HMMs of corresponding foreign phones. In a recent multilingual TTS study [26], the accent level can be controlled by varying the domain adversarial weight [26]. In another attempt [27], accent is manipulated via tone or stress embedding input. Accent as perceived in human speech is subtle and at a fine level. In the prior attempts to control the accent intensity, there is no direct and measurable correlation between the controlling factor and the natural accent intensity. The question is how to characterize the accent intensity, and employ the intensity to control the synthesis of L2 speech, which is another focus of this paper.

In this paper, we propose a neural TTS solution with controllable accent and its intensity, that is referred to as the CAI-TTS system. We address the above two challenges by studying three novel mechanisms. 1) An accent variation adaptor that models the complex accent variance. The accent variation adaptor seeks to project the L2 speaker identity (ID),
L2 accent identity and its intensity into the output speech at a phoneme level. 2) An accent intensity modeling scheme that uses relative attribute [28] technique to automatically learn the relationship between L1 and L2 speech, thus quantifying the accent intensity for L2 speech. 3) A consistency constraint module that ensures the synthesized L2 speech manifests the expected accent intensity precisely.

During run-time inference, the CAI-TTS system takes the L2 speaker ID, L2 ID and its intensity along with the phoneme sequence as input, and outputs the L2 speech with the expected accent intensity, thereby regulating the accented speech generation explicitly. The significant contributions of this work include,

- We introduce a novel accented TTS synthesis paradigm that explicitly controls the accent and its intensity in output speech.
- We successfully design and implement a neural architecture, CAI-TTS, with three novel mechanisms.
- We show that the proposed CAI-TTS framework outperforms the baseline models and generates high-quality L2-accented speech.

The rest of this paper is organized as follows. In Section II, we discuss the background to motivate our work. In Section III, we propose the CAI-TTS framework. We report the experimental results in Section IV. Finally, Section V concludes the study.

II. RELATED WORK

A. Accent Variance Learning

Recently, much progress was made in neural TTS for L1 speech [8]–[11], [29], [30]. However, the state-of-the-art models are not designed to deal with accent variance. In speech analysis, there has been study on prosodic variance of speech in terms of pitch and energy [31]. Pitch is a key feature that characterizes speech variance, and has a great impact on perceptual quality of speech [22]. Energy indicates frame-level magnitude of mel-spectrum and directly affects the loss computed on mel-spectrum. There have been valuable attempts towards learning the variance information. For example, in FastSpeech2 [1], a variance adaptor is introduced, which has a pitch and an energy predictor, to learn the speech variance at frame-level. However, L2 speech is far more complex in terms of speaking style and variation than L1 speech, that calls for further study of two research problems.

The first problem is how to represent an accent. The L1 variance adaptor is not explicitly trained to encode accent information. The second problem is the characterization of accent variance. It is believed that phoneme-level acoustic features are more accent informing than frame-level features [22], [32], [33]. There have been studies to model the prosodic variance for phonemes, such as FastPitch [22]. However, FastPitch doesn’t model the energy. Addressing the above two problems, we propose a novel accent variance adaptor, which encodes L2 speaker, L2 accent, and its intensity, and predicts phoneme-level pitch, energy and duration.

B. Attribute Ranking

Attribute ranking learns the difference between two samples that are significantly different in a particular attribute. It has been widely studied in computer vision [28], [34]–[36]. Parikh et al. [28] first proposed the concept of “relative attributes” in which pairs of visual entities can be compared, with respect to their relative strength of any specific attribute. With a set of paired samples, they learn a global ranking function for each attribute that can be used to compare a pair of new samples respective to the target attribute. Bringing this idea forward, we propose to compare the acoustic features from a pair, <L1, L2>, of speech samples of the same speaker and determine the difference between them to quantify the accent intensity.

In emotional TTS synthesis [37], [38], the idea of relative attributes has been explored. However, accented TTS presents us a new challenge. In emotional TTS, the <neutral, emotional> paired speech is available for emotion strength learning. However, the reference L1 speech sample is not available for accent intensity modeling. Learning of ranking functions is not possible without parallel data. Furthermore, the specific acoustic representations of emotion and accent attributes are completely different, that calls for a new solution to the problem.

In this work, we start with a L2 speech corpus, and construct a <L1, L2> paired speech corpus by synthesizing high-quality L1 speech for each L2 speaker. We introduce a ranking function learning method to model the accent intensity from the <L1, L2> corpus.

C. Controllable Expressive TTS

There are two general approaches to synthesize expressive speech. 1) Global speaking style: The speaking style can be obtained from a reference utterance, or a manual setting. Wang et al. [39] adopt a reference encoder to derive a style embedding from an input utterance as a linear combination of some basis style vectors. Others [26], [40]–[42] use the variational autoencoder (VAE) to model latent representations for styles and prosody of speech. 2) Token-wise fine-grained prosody embeddings: In FastSpeech2 [1], a variance adaptor is studied to add the variance information (e.g., duration, pitch, energy, etc.) to the phoneme hidden sequence in a way to generate expressive speech. Furthermore, more variance information has been added in the variance adaptor, such as emotion [43]–[45] and style [24], [46], [47] to control the fine-grained expressiveness accordingly.

Strictly speaking, the above techniques don’t really control the accent rendering. At run-time inference, the system generates the output speech by conditioning on the style embedding or the variance model. In this way, the speech is synthesized to follow a given style or prosody pattern. There is a lack of direct control over the synthesized speech, and there is no measurable correlation between the controlling factor and the intended accent intensity.

To the best of our knowledge, there has no intuitive method for controlling the fine-grained accent in the literature. Motivated by the previous findings, we propose a novel neural
architecture that quantitatively controls the accent and its intensity for the first time.

III. CAI-TTS NEURAL ARCHITECTURE

We propose a neural architecture, termed as CAI-TTS, as shown in Fig. 1 (a) that consists of a text encoder, an accent variance adaptor, a mel-spectrum decoder, an additional accent intensity predictor and an universal HiFi-GAN vocoder. The text encoder encodes the input phoneme sequence into phoneme embedding. The accent variance adaptor modulates the input phoneme embeddings towards the target accent. The mel-spectrum decoder converts the modulated phoneme embeddings into a mel-spectrum sequence. Note that the accent intensity of the output L2 speech is estimated from the generated mel-spectrum sequence by the additional accent intensity predictor during CAI-TTS training. We impose a consistency constraint loss to minimize the difference between the estimated accent intensity and the expected intensity. Finally, the universal HiFi-GAN vocoder was used to synthesize high-quality L2 speech.

The text encoder and mel-spectrum decoder share a similar architecture with FastSpeech2 [1]. We use the feed-forward Transformer block, which is a stack of self-attention [48] layer and 1D-convolution, as the basic structure. We denote the text encoder as $E_t(\cdot)$, which produces the phoneme hidden representation $H_{ph} = E_t(P + PE)$, where $P$ is the phoneme sequence, and $PE$ is a triangle positional embedding [48] to indicate the positional information.

In Sec. III-A, we will introduce the details of the accent variance adaptor and the consistency constraint for accent intensity predictor. Note that the most important input of accent variance adaptor, that is accent intensity, is obtained through the pre-training step, termed as “accent intensity modeling”. Therefore, in Sec. III-A, we will demonstrate the workflow of the accent intensity modeling on the available L2 speech corpus. At last, the run-time inference will be explained.

A. Accent Variance Adaptor

The traditional variance adaptor in [1] just adds different variance information such as duration, pitch and energy into the hidden sequence to predict the mel-spectrogram features, that lacks a controlling mechanism. Next we introduce an accent variance adaptor to provide accent information according to the accent intensity. Specifically, we fuse the L2 speaker identity, accent identity and its accent intensity before the prediction of pitch, energy and duration. In other words, the accent variance adaptor learns to project the desired accent and its intensity into the input phoneme embedding $H_{ph}$. This enables all variables, namely the pitch, energy, and duration, to be regulated by the fine-grained accent intensity. Note that the duration predictor is located at the end of the accented variance adaptor instead of the beginning of the variance adaptor in the original FastSpeech2 [1]. It was reported that it is more effective to render accent at phoneme-level than frame-level [22].

As shown in Fig. 1(b), the adaptor consists of 1) a L2 speaker encoder, 2) a L2 accent encoder, 3) an intensity encoder, 4) a phoneme pitch predictor, 5) a phoneme energy predictor, and 6) a phoneme duration predictor.

- **L2 Speaker Encoder**: The L2 speaker encoder is a learnable lookup table, that encodes the L2 speaker...
identity $s$ into a speaker code, $e_s = E_{spk}(s)$ [5], [6], to represent a speaker.

- **L2 Accent Encoder**: Similarly, the L2 accent encoder $E_{acc}(\cdot)$ is another learnable lookup table that transforms an L2 accent category $a$ into an accent embedding, $e_a = E_{acc}(a)$.

- **Intensity Encoder**: The intensity encoder $E_{int}(\cdot)$ is a linear layer that transforms a real-valued accent intensity scalar $i$ to an embedding vector, $e_i = E_{int}(i)$. The real-value scalar of accent intensity is generated by a novel pre-training module, named “accent intensity modeling”, which will be described in Sec. III-C.

As shown in Fig. 1(b), we concatenate [44] the accent embedding $e_a$ and its intensity $e_i$, which is then summed with the speaker code $e_s$ and the $H_{ph}$ to form an accented phoneme embedding $H'_{ph}$.

- **Variance Predictors**: With the accented phoneme embeddings, we would like to predict three key prosodic elements that characterize accents, i.e. pitch, energy and duration of phonemes. The phoneme pitch and energy predictors take $H'_{ph}$ as input and generate the pitch and energy embedding $p$, $e$. The two predictors share a similar architecture, that has a 2-layer 1D-convolutional network, a fully connected (FC) layer and an extra 1D-convolutional network.

To train the predictors, we first extract the frame-level pitch from the voiced speech frame, and set it to 0 for unvoiced frames. We compute the L2-norm of the amplitude of each short-time Fourier transform (STFT) frame as the energy. We obtain frame-level pitch and energy averages for each phoneme using the ground-truth duration $D$. The phoneme pitch and energy scalars are normalized to zero mean and unit variance over all training data, to serve as the supervision signals. We define mean square error loss $L_{p,pitch}$ and $L_{p,energy}$ behind the FC layers as the objective functions for the training of the pitch and energy predictors. Unlike in FastSpeech2 [1] where the phoneme duration predictor takes the encoder output directly as input, our phoneme duration predictor takes the accented phoneme embedding $H'_{ph}$ as input and is expected to output more accurate phoneme duration $D$. At last, we sum the accented phoneme, pitch and energy embeddings to form an accented phoneme embedding $H''_{ph} = H'_{ph} + p + e$. A length regulator (LR) is used to transform the $H'_{ph}$ to frame-level embeddings $H_{fm}$ based on the predicted phoneme duration $D$. Finally, the mel-spectrum decoder converts the $H_{fm}$, along with a triangle positional embedding $PE$ [48], into a mel-spectrum sequence.

**B. Consistency Constraint for Accent Intensity**

The consistency constraint module ensures the synthesized L2-accented speech manifests the expected accent intensity at a fine level, as shown in Fig. 1(a). The consistency constraint is applied via a consistency constraint loss $L_{cc}$ between the intended accent intensity $i$ and the accent intensity $\hat{i}$ measured by the accent intensity predictor, i.e., $L_{cc} = \text{MSE}(i, \hat{i})$.

The accent intensity predictor consists of a bi-directional recurrent neural network layer with Gated Recurrent Unit (GRU), that is followed by an FC layer. It is trained in a supervised manner together with the CAI-TTS model subject to the total loss, $L_{final} = L_{mel} + L_{dur} + L_{p,pitch} + L_{p,energy} + L_{cc}$, where $L_{mel}$ and $L_{dur}$ are the MSE loss for mel-spectrum and duration loss as in FastSpeech2 [1].

**C. Accent Intensity Modeling**

The key to accent control at a fine level is to find a descriptor to quantify the accent intensity. To this end, we propose a novel pre-training strategy, named “accent intensity modeling” scheme, that seeks to quantify the accent intensity for each sample of L2-accented speech before CAI-TTS training, as illustrated in Fig. 2. The accent intensity modeling scheme consists of L1 speech generation and ranking function learning. The ranking function learning includes accent feature extraction and ranking function training.

Note that L1 speech generation aims to develop a <L1, L2> paired speech dataset, that is used for the ranking function learning. Then the ranking function learning will learn the difference between L1 and L2 speech pair to quantify the accent intensity for L2 speech. We will introduce the workflow in order.

1) **L1 Speech Generation**: We first create a <L1, L2> parallel speech database of the same speech content, where an L1 speech sample is synthesized for each L2 utterance of the same speaker by SC-GlowTTS [49], a state-of-the-art zero-shot TTS model as in Fig. 3. The high-quality L1 speech samples serve as the reference for the ranking function learning.

As in [49], the SC-GlowTTS model employs an external speaker extractor, that encodes an utterance into a speaker embedding. We adopt the flow-based non-autoregressive model to predict the mel-spectrum sequence. Finally, a HiFi-GAN [14] vocoder converts the output mel-spectrum sequence to speech waveform.

In practice, for a text-speech pair in the accented TTS corpus, we first obtain a phoneme-speech pair $\{P, Y\}$ where...
We assume that two samples from the same domain (L1 or L2) are respectively, according to the following relative constraints:

\[
\begin{align*}
F_m &> F_h, \quad \forall (m, h) \in O \\
F_m &\leq F_h, \quad \forall (m, h) \in S
\end{align*}
\]

where we weight \( F_m \) and \( F_h \) with a learnable weighting vector \( \mathbf{w} \) and return a weighted sum \( i \) indicating the accent intensity of sample \( m \).

To achieve this, we first build two sets, that are \( O \) and \( S \), which contains ordered and similar paired samples respectively, according to the following relative constraints:

\[
\begin{align*}
\forall (m, h) \in O : \mathbf{w}F_m &> \mathbf{w}F_h \\
\forall (m, h) \in S : \mathbf{w}F_m = \mathbf{w}F_h
\end{align*}
\]

where \( \mathbf{F} \) represents a sample from the union of \( f^{L2} \) and \( f^{L2} \): \( \mathbf{F} \in \{ f^{L1} \cup f^{L2} \} \).

Specifically, we pick up one sample \( \mathbf{F}_m \) from \( f^{L1} \) and another sample \( \mathbf{F}_h \) from \( f^{L2} \) to build the ordered set \( O \). We expect that the accent intensity of the L2-accented sample \( \mathbf{F}_h \) is higher than that of the L1 sample \( \mathbf{F}_m \). For the similar set \( S \), we pick up two samples \( \mathbf{F}_m \) and \( \mathbf{F}_h \) from \( f^{L1} \) (or \( f^{L2} \)). We assume that two samples from the same domain (L1 or L2) have similar accent intensities.

Next, we can learn a support vector machines (SVM) [51] to estimate \( \mathbf{w} \) by solving the following optimization problem:

\[
\begin{align*}
\text{minimize} & \left( \frac{1}{2} ||\mathbf{w}||^2 + C \left( \sum \xi_i + \sum \eta_i \right) \right) \\
\text{subject to} & \quad w(F_m - F_h) \geq 1 - \xi_{mh}, \forall (m, h) \in O \\
& \quad |w(F_m - F_h)| \leq \eta_{mh}, \forall (m, h) \in S \\
& \quad \xi_{mh} \geq 0; \eta_{mh} \geq 0
\end{align*}
\]

where \( C \) is to control the trade-off between the margin and the size of the slack variables \( \xi_{mh} \) and \( \eta_{mh} \). The use of \( \xi_{mh} \) and \( \eta_{mh} \) is to relax the constraints on classifying all of the ordered and similar samples in \( O \) and \( S \), respectively. This primal problem can be solved by the Newton’s method [52]. Note that the intensity scalar \( i \) is normalized to \((0,1)\) with 1 as the highest intensity.

D. Run-time Inference

At run-time, the CAI-TTS architecture takes Input text, L2 speaker ID, L2 accent ID and the custom accent intensity as input to generate the output L2 speech with the help of universal HiFi-GAN vocoder [14] in this paper.

Note that the predicted pitch contour and energy also can be modified during inference to control certain perceived qualities of the generated speech like FastPitch [22] etc. However, synthesized speech with a large pitch (or energy) shift scale suffers from audio quality degradation, and speaker characteristics deformation [53]. In our work, we just try to modify the L2 speaker ID, accent ID and accent intensity to achieve accented and intensity controllable TTS synthesis.

IV. EXPERIMENTS

We evaluate CAI-TTS through accented text-to-speech synthesis experiments

A. Datasets

We train CAI-TTS on the publicly available L2-ARCTIC corpus [54], which includes about 26 hours recordings of accented English from 24 non-native speakers, whose are native in Hindi, Korean, Mandarin, Spanish, Arabic and Vietnamese. Two male and two female speakers contributed in each language.

In L2-ARCTIC, scripts and their phoneme-level duration annotations are provided. The scripts for each speaker consists of about 1,130 utterances, resulting in about 27,120 utterances in total. Its phonetic transcription follows the ARPAbet phoneme set. The speech data are sampled at 44.10kHz and coded in 16 bits. For each accented speaker, we partition the speech data into training, validation, and test set at a ratio of 8:1:1.

1Audio samples: https://speechdemo.github.io/caitts
2http://www.speech.cs.cmu.edu/cgi-bin/cmudict
B. Comparative Study

This work is one of the first attempts to control multiple accents and their intensity at a fine level. As there is no reference system in the literature, we choose some state-of-the-art TTS systems as the benchmark. 1) GT (oracle): This is the natural L2 speech by the speakers; 2) GT mel + HiFi-GAN (oracle): This is the synthesized speech with a HiFi-GAN vocoder using GT mel-spectrum; 3) Tacotron2: This is a multi-speaker Tacotron2 [9] model which learns a look-up-table to map embeddings for different speaker identity; 4) Transformer-TTS: This is a multi-speaker Transformer-TTS [55] model which learns a look-up-table to map embeddings for different speaker identity; 5) FastSpeech2: This is a multi-speaker FastSpeech2 [1] model which learns a look-up-table to map embeddings for different speaker identity; 6) CAI-TTS (proposed): This is our proposed model. We also develop 3 variants of CAI-TTS model for an ablation study. 7) CAI-TTS w/o accent intensity: We replace the accent variance adaptor with the variance adaptor of FastSpeech2 [1]; 8) CAI-TTS w/o phoneme pitch & energy: We replace the phoneme level pitch and energy predictors with frame-level pitch and energy predictors as in [1]; 9) CAI-TTS w/o consistency constraint: We remove the consistency constraint module from the CAI-TTS model.

C. Experimental Setup

The text encoder and mel-spectrum decoder use 6 Feed-Forward Transformer (FFT) blocks. Note that the text encoder takes the 256 dimensional phoneme embedding as input. The mel-spectrum decoder generates 80-channel mel-spectrum, which is extracted with 12.5ms frame shift and 50ms frame length, as output. We downsample all speech files to 22.05kHz and trimmed leading and trailing silence.

The L2 speaker and accent encoders employ two lookup tables with $14 \times 256$ and $6 \times 128$ respectively. The intensity encoder consists of a linear layer, which encodes the accent intensity scalar into a 128 dimensional intensity embedding.

Following [22], we represent the pitch and energy scalar in linear scale. The pitch and energy predictors employ a Conv1D with kernel size 3 and 384/256 channels, Conv1D with 256/256 channels, and an FC layer to project a 256-channel vector into a single pitch/energy scalar, and the last Conv1D layer with kernel size 9 to upsamples pitch/energy scalar to pitch/energy embeddings. We use Dropout rate of 0.5 in every Dropout layer. The accent intensity predictor in consistency constraint module consists of a GRU layer with hidden size 128 and an FC layer to output the intensity scalar.

We use the Adam optimizer [56] with $\beta_1 = 0.9$, $\beta_2 = 0.98$ and follow the same learning rate schedule in [48]. All models are trained with 900k steps to ensure complete convergence. The codes are written in Python 3.6 using the Pytorch library 1.7.0. The GPU type is NVIDIA Quadro RTX 6000 with 24GB GPU memory. For a fair comparison, we adopt the same pretrained universal HiFi-GAN [14] vocoder for all systems. As the universal HiFi-GAN vocoder is trained on a collection of multiple dataset, that includes LJSpeech [57], VCTK [58] and LibriTTS [59], it is known to produce high-quality voice for unseen speakers [60], [61].

D. Audio Quality of Generated L1 Speech

The accent intensity modeling cannot be done well without L1 speech with high audio quality. Therefore, we first conduct a Mean Opinion Score (MOS) and a Speaker Similarity MOS (SMOS) evaluation to validate the overall performance of the L1 speech generated by zero-shot TTS in terms of audio quality and speaker similarity.

Specifically, we conduct listening experiments with mean opinion score (MOS) for audio quality and similarity MOS (SMOS) [62] for speaker similarity. Both metrics are rated in 1-to-5 scale and reported with 95% confidence intervals (CI).

We first conduct MOS listening experiments to compare the overall audio quality between L2 speech and synthesized L1 speech. 100 <L1, L2> pairwise sentences were chosen as the test samples randomly. We invite 20 subjects to rate the audio quality for each sample. Each listener listened to 200 speech samples. The MOS values are calculated by taking the arithmetic average of all scores provided by the subjects. To this end, the MOS score of L2 speech reaches $4.57 \pm 0.03$, and the MOS score of synthesized L1 speech achieves $4.32 \pm 0.02$. Note that both MOS scores are higher than 4.0, indicating that the quality of synthesized L1 speech is good enough to serve as the reference speech for accent intensity modeling.

We also evaluate the speaker similarity between L1 and L2 speech. We follow the MOS experiment settings, except that we randomly choose 100 samples as reference samples which share same speaker identity with the test samples. 20 listeners are invited to listen to the reference samples and test samples, and rate the speaker similarity for each test sample. After that, we calculate the average SMOS according to all scores. Note that the SMOS scores of L1 and L2 speeches got $4.25 \pm 0.03$ and $4.49 \pm 0.01$ respectively, which are very similar to the trending of MOS scores. We believe that the synthesized L1 speech generated by zero-shot TTS performs enough speaker similarity.

In a nutshell, the synthesized L1 speech achieves comparable scores with L2 speech on both experiments in terms of audio quality and speaker similarity, which shows the effectiveness of the zero-shot TTS model for L1 speech generation. In other words, we observe that the quality of the synthesized L1 speech is on par with the L2-accented speech in both experiments. Therefore, we confirm that the <L1, L2> paired speech samples are adequate for accent intensive learning study.

E. Audio Quality of CAI-TTS

In this section, we conduct objective and subjection evaluations to validate the overall audio quality of our CAI-TTS model in terms of accented expression.

In the objective evaluation, we first employ Mel Cepstral Distortion (MCD) to measure the spectral distance between the synthesized and reference Mel-spectrum features. Since the sequences are not aligned, we perform Dynamic Time Warping (DTW) algorithm [63] to align the sequences prior
TABLE I: The comparison of the audio quality for different systems in terms of MCD in objective experiments, MOS and BWS in subjective experiments.

| System                          | Audio Quality |  |  |  |  |
|---------------------------------|---------------|---------------|---------------|---------------|---------------|
|                                 | MCD (dB)      | MOS           | BWS Evaluation | Best (%)      | Worst (%)     |
| GT (Mel + HiFi-GAN)             | NA            | 4.62 ± 0.02   | NA            | NA            | NA            |
| GT                              | NA            | 4.59 ± 0.03   | NA            | NA            | NA            |
| Tacotron2 [9] (Mel + HiFi-GAN)  | 6.57          | 4.33 ± 0.01   | 4             | 6             | 34            |
| Transformer TTS [10] (Mel + HiFi-GAN) | 6.43          | 4.35 ± 0.02   | 8             | 22            |
| FastSpeech2 [11] (Mel + HiFi-GAN) | 6.31          | 4.38 ± 0.03   | 5             | 18            |
| CAI-TTS (proposed) (Mel + HiFi-GAN) | 6.08          | 4.57 ± 0.01   | 45            | 4             |
| w/o phoneme pitch & energy      | 6.11          | 4.52 ± 0.02   | 9             | 8             |
| w/o accent intensity            | 6.14          | 4.48 ± 0.03   | 13            | 6             |
| w/o consistency constraint      | 6.16          | 4.43 ± 0.01   | 14            | 8             |

TABLE II: The comparison of the accent variance information for different systems, including standard deviation ($\sigma$), skewness ($\gamma$), kurtosis ($K$) and average dynamic time warping (DTW) distances ($\varrho$) for pitch, mean absolute error (MAE) for energy and the average of absolute boundary differences ($\Delta$) for duration.

| System                          | Accent Variance |  |  |  |  |  |
|---------------------------------|-----------------|---------------|---------------|---------------|---------------|
|                                 | Pitch           | Energy        | Duration      |
|                                 | $\sigma$ | $\gamma$ | $K$ | $\varrho$ | MAE | Δ (ms) |
| GT (Mel + HiFi-GAN)             | 49.8         | 0.627        | 0.854        | NA            | NA            | NA            |
| GT                              | 49.5         | 0.629        | 0.852        | 15.27         | 0.192         | NA            |
| Tacotron2 [9] (Mel + HiFi-GAN)  | 32.5         | 0.906        | 1.212        | 19.80         | 0.297         | 22.12         |
| Transformer TTS [10] (Mel + HiFi-GAN) | 35.8         | 0.887        | 1.025        | 19.32         | 0.288         | 21.98         |
| FastSpeech2 [11] (Mel + HiFi-GAN) | 43.2         | 0.752        | 0.973        | 18.01         | 0.274         | 20.08         |
| CAI-TTS (proposed) (Mel + HiFi-GAN) | 48.9         | 0.613        | 0.882        | 16.78         | 0.235         | 18.54         |
| w/o phoneme pitch & energy      | 48.3         | 0.610        | 0.896        | 17.06         | 0.240         | 18.72         |
| w/o accent intensity            | 47.9         | 0.611        | 0.890        | 16.95         | 0.239         | 18.70         |
| w/o consistency constraint      | 47.8         | 0.594        | 0.889        | 17.13         | 0.245         | 18.85         |

to comparison. Lower MCD value indicates smaller distortion, thus better quality. We randomly select 100 utterances from the test set as test samples and report the results in the second column of Table I. We observe that the CAI-TTS outperforms all other systems with the lowest MCD of 6.08 dB. In the ablation study, we observe that the three ablation systems see a performance degradation to some extent, which reaffirms the effectiveness of the individual prosody-controlling modules.

In the subjective experiment, we first evaluate all systems in terms of MOS. We choose 100 utterance as the test samples. 20 listeners were participated and each listener listens to 100 speech samples. As shown in the third column of Table I, it is observed that our CAI-TTS achieves a MOS of 4.57 ± 0.01, that is significantly higher than others and very close to those of the GT (Mel+HiFi-GAN) and GT.

We conduct the second listening experiment through Best Worst Scaling (BWS) [64], which is an effective method to provide a ranking of a long list of listening samples. BWS evaluation share same test samples with previous MOS evaluation. For each utterance, seven speech samples produced by these seven TTS systems (expect GT(Mel+HiFi-GAN) and GT) form a group. 20 listeners were participated and each listener picks the best and worst samples in terms of naturalness for each group. We report the results in the last two columns of Table I. We observe that CAI-TTS is selected for 45% of time as the best model and 4% as the worst model. All baselines get lower best percentage and higher worst percentage. The results suggest that the listeners have a clear preference towards our proposed CAI-TTS system in terms of accent similarity.

F. Accent Variance Learning

To understand how the accent variance adaptor performs, we randomly select 100 utterances from the test set as the test samples.

Pitch: We follow [1] and compute the moments (including standard deviation ($\sigma$), skewness ($\gamma$) and kurtosis ($K$)), and average DTW distance ($\varrho$) of the pitch distribution between the synthesized L2-accented speech and the ground truth reference. The results are summarized in the second to fifth columns of Table II. It can be seen that the CAI-TTS system is reported with the moments ($\sigma$, $\gamma$ and $K$) that are closer to those of the natural speech (GT) than Tacotron2, Transformer TTS and FastSpeech2. In terms of the average DTW distance $\varrho$ to the ground truth pitch, the CAI-TTS system outperforms all baselines, with the lowest value of 16.78.

Energy: We also compute the accuracy by calculating the mean absolute error (MAE) between the frame-level energy
Fig. 4: Confusion matrices between perceived and intended accent intensity categories of synthesized speech. (a) CAI-TTS; b) CAI-TTS w/o consistency constraint. The X-axis and Y-axis of the figures represent the perceived and intended category, namely slight, average, and strong.

extracted from the synthesized and the ground-truth L2-accented speech. The DTW algorithm is applied to align the paired sequences. As shown in the sixth column of Table II, the CAI-TTS system presents the lowest MAE among all benchmarking baselines.

**Duration:** We also evaluate the quality of phoneme duration by calculating the distance [1] between the predicted duration and the ground-truth duration at a phoneme level. Note that the accented TTS corpus have provided the phoneme level duration. For speech generated by Tacotron2 and Transformer TTS, we extract the phoneme duration from the trained attention alignment. For speech generated by FastSpeech2 and CAI-TTS, we obtain the duration from duration predictor output directly. The seventh column of Table II shows that CAI-TTS generates more accurate phoneme duration than all benchmarking baselines.

**G. Controllable Accent Intensity**

We further evaluate the ability of CAI-TTS to adjust the L2 accent intensity of the synthesized accented speech by comparing CAI-TTS with the CAI-TTS w/o consistency constraint.

We first conduct an intensity classification experiment. At run-time, we assign the L2 speaker ID, accent ID and its intensity from 0.1 to 0.9 to synthesize the L2-accented speech with various accents. We consider the intensity scalars from 0.1 to 0.3 as ‘slight’, 0.4 to 0.6 as ‘average’ and 0.7 to 0.9 as ‘strong’ in three categories. We select 100 utterances from the test set, resulting in 100 samples for both systems. Accordingly, all listeners are instructed to rate the accent intensity category, that are ‘slight’, ‘average’ or ‘strong’, for each sample. A listener can listen to the samples multiple times when needed.

Fig. 4 presents the intensity confusion matrices. It is observed that the CAI-TTS system shows a higher correlation between the perceived and intended accent intensity categories, with a correlation of over 80%, that is considered a competitive result against other intensity-controlled studies. Furthermore, the CAI-TTS system clearly outperforms the contestant. The experiments confirm the superiority of the proposed controllable intensity mechanism.

We further evaluate the intensity-controlled speech at a fine level. For each utterance, nine speech samples with intensity from 0.1 to 0.9 produced by CAI-TTS and CAI-TTS w/o consistency constraint form two groups. We invite 20 listeners, each listening to all samples in an increasing order of accent intensity. The confusion matrices are reported in Fig. 5. We observe that the proposed CAI-TTS system provides a higher correlation between the perceived and the intended fine categories than the contestant. All subjective evaluations show consistently results that the CAI-TTS system provides an effective fine level intensity control.

**V. CONCLUSION**

We have studied a novel TTS model, named CAI-TTS, to control the L2 accent and its intensity during the speech generation. We have conducted a series of experiments on audio quality, accent variance and intensity control to validate the effectiveness of the CAI-TTS model. The proposed CAI-TTS consistently outperforms all baselines in terms of accent...
rendering and the control of its intensity. This work marks an important step towards controllable rendering of accented TTS synthesis. For future work, we plan to extend CAI-TTS to support fine-grained (e.g., phoneme level) accent control.

REFERENCES

[1] Y. Ren, C. Hu, X. Tan, T. Qin, S. Zhao, Z. Zhao, and T.-Y. Liu, “Fastspeech 2: Fast and high-quality end-to-end text to speech,” in International Conference on Learning Representations, 2020.

[2] R. Liu, B. Sisman, G. Gao, and H. Li, “Expressive tts training with frame and style reconstruction loss,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 29, pp. 1806–1818, 2021.

[3] 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,” in 9th ISCA Speech Synthesis Workshop, 2016, pp. 125–125.

[4] S. O. Aruk, M. Chrzanowski, A. Coates, G. Diamos, A. Gibiansky, Y. Kang, X. Li, J. Miller, A. Ng, J. Raiman et al., “Deep voice: Real-time neural text-to-speech,” in International Conference on Machine Learning. PMLR, 2017, pp. 195–204.

[5] A. Gibiansky, S. Arik, G. Diamos, J. Miller, K. Peng, W. Ping, J. Raiman, and Y. Zhou, “Deep voice 2: Multi-speaker neural text-to-speech,” Advances in neural information processing systems, vol. 30, pp. 295–299.

[6] W. Ping, K. Peng, A. Gibiansky, S. O. Arik, A. Kannan, S. Narang, J. Raiman, and J. Miller, “Deep voice 3: Scaling text-to-speech with convolutional sequence learning,” in International Conference on Learning Representations, 2018.

[7] J. Sotelo, S. Mehri, K. Kumar, J. F. Santos, K. Kastner, A. C. Courville, J. Raiman, and Y. Zhou, “Deep voice 2: Multi-speaker neural text-to-speech,” Advances in neural information processing systems, vol. 30, pp. 295–299.

[8] Y. Zhang, R. J. Weiss, H. Zen, Y. Wu, Z. Chen, R. Skerry-Ryan, J. Yia, A. Rosenberg, and B. Ramabhadran, “Learning to speak fluently in a foreign language: Multilingual speech synthesis and cross-language voice cloning,” Proc. Interspeech 2019, pp. 2080–2084, 2019.

[9] Z. Liu and B. Mak, “Multi-lingual multi-speaker text-to-speech synthesis for voice cloning with online speaker enrollment,” in INTERSPEECH, 2020, pp. 2932–2936.

[10] D. Parikh and K. Grauman, “Relative attributes,” in 2011 International Conference on Computer Vision. IEEE, 2011, pp. 503–510.

[11] N. Li, Y. Liu, Y. Wu, S. Liu, S. Zhao, and M. Liu, “Robutrans: A robust transformer-based text-to-speech model,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 05, 2020, pp. 8228–8235.

[12] S.-H. Lee, H.-W. Yoon, H.-R. Noh, J.-H. Kim, and S.-W. Lee, “Multi-spectrogram: High-diversity and high-fidelity spectrogram generation with adversarial style combination for speech synthesis,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, no. 14, 2021, pp. 13 198–13 206.

[13] K. Eyben, M. Wöllmer, and B. Schuller, “Opensmile: the munich package for automatic speech, speaker, and audio scene analysis,” in Proceedings of the 18th ACM international conference on Multimedia, 2010, pp. 1459–1462.

[14] Z. Zhu, S. Yang, G. Yang, and L. Xie, “Diverse and controllable speech synthesis with gmm-based phone-level prosody modelling,” in Proc. Interspeech 2021, 2021, pp. 5–10.

[15] B. Siddique, R. S. Feris, and L. S. Davis, “Image ranking and retrieval based on multi-attribute queries,” in CVPR 2011. IEEE, 2011, pp. 801–808.

[16] Z. Meng, N. Adhura, H. J. Kim, G. Fung, and V. Singh, “Efficient relative attribute learning using graph neural networks,” in Proceedings of the European conference on computer vision (ECCV), 2018, pp. 552–567.

[17] Y. Saqui1, Q.-C. Xu, Y.-L. Yang, and P. Hall, “Rank3dan: Semantic mesh generation using relative attributes,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 04, 2020, pp. 5586–5594.

[18] X. Zhu, S. Yang, G. Yang, and L. Xie, “Controlling emotion strength with relative attribute for end-to-end speech synthesis,” in 2019 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), 2019, pp. 192–199.

[19] Y. Lei, S. Yang, and L. Xie, “Fine-grained emotion strength transfer, control and prediction for emotional speech synthesis,” in 2021 IEEE Spoken Language Technology Workshop (SLT). IEEE, 2021, pp. 423–430.
in International Conference on Machine Learning. PMLR, 2018, pp. 5180–5189.

[40] W.-N. Hsu, Y. Zhang, R. J. Weiss, H. Zhen, Y. Wu, Y. Wang, Y. Cao, Y. Jia, Z. Chen, J. Shen et al., “Hierarchical generative modeling for controllable speech synthesis,” in International Conference on Learning Representations, 2018.

[41] G. Sun, Y. Zhang, R. J. Weiss, Y. Cao, H. Zhen, and Y. Wu, “Fully-hierarchical fine-grained prosody modeling for interpretable speech synthesis,” in ICASSP 2020-2020 IEEE international conference on acoustics, speech and signal processing (ICASSP). IEEE, 2020, pp. 6264–6268.

[42] Z. Liu, Q. Tian, C. Hu, X. Liu, M. Wu, Y. Wang, H. Zhao, and Y. Wang, “Controllable and robustless non-autoregressive end-to-end text-to-speech,” arXiv preprint arXiv:2207.06088, 2022.

[43] S. Sivaprasad, S. Kosgi, and V. Gandhi, “Emotional prosody control for speech generation,” in Interspeech 2021, 22nd Annual Conference of the International Speech Communication Association, Brno, Czechia, 30 August - 3 September 2021, H. Hermansky, H. Cernocky, L. Burget, L. Lamel, O. Scharenborg, and P. Motlicek, Eds. ISCA, 2021, pp. 4653–4657.

[44] C.-B. Im, S.-H. Lee, S.-B. Kim, and S.-W. Lee, “Emoq-tts: Emotion intensity quantization for fine-grained controllable emotional text-to-speech,” in ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2022, pp. 6317–6321.

[45] Z. Zhang, Y. Qin, W. Zhang, J. Wu, M. Li, Y. Gai, F. Jiang, and T. Lee, “Iemott: Toward robust cross-speaker emotion transfer and control for speech synthesis based on disentanglement between prosody and timbre,” arXiv preprint arXiv:2206.14866, 2022.

[46] K. Lee, K. Park, and D. Kim, “Styler: Style factor modeling with rapidity and robustness via speech decomposition for expressive and controllable neural text to speech,” in Interspeech 2021. ISCA, 2021.

[47] T. Raitio, J. Li, and S. Seshadri, “Hierarchical prosody modeling and control in non-autoregressive parallel neural tts,” in ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2022, pp. 7587–7591.

[48] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in Advances in neural information processing systems, 2017, pp. 5998–6008.

[49] E. Casanova, C. Shulby, E. Golge, N. M. Muller, F. S. de Oliveira, A. C. Junior, A. d. S. Soares, S. M. Aluisio, and M. A. Ponti, “Sc-glowtts: an efficient zero-shot multi-speaker text-to-speech model,” in Proc. Interspeech 2021, 2021, pp. 1–5.

[50] D. L. Bolinger, “A theory of pitch accent in english,” Word, vol. 14, no. 2–3, pp. 109–149, 1958.

[51] T. Joachims, “Optimizing search engines using clickthrough data,” in Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining, 2002, pp. 133–142.

[52] O. Chapelle, “Training a support vector machine in the primal,” Neural computation, vol. 19, no. 5, pp. 1155–1178, 2007.

[53] T. Bak, J.-S. Bae, H. Bae, Y.-J. Kim, and H.-Y. Cho, “Fastpitchformat: Source-filter based decomposed model for speech synthesis,” in arXiv preprint arXiv:2106.15127, 2021.

[54] G. Zhao, S. Sosanta, A. Silpachai, I. Lucic, E. Chukharev-Hudilainen, J. Levis, and R. Gutierrez-Osuna, “L2-arcitic: A non-native english speech corpus,” Proc. Interspeech 2018, pp. 2783–2787, 2018.

[55] M. Chen, X. Tan, Y. Ren, J. Xu, H. Sun, S. Zhao, and T. Qin, “Multispeech: Multi-speaker text to speech with transformer,” Proc. Interspeech 2020, pp. 4024–4028, 2020.

[56] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[57] K. Ito and L. Johnson, “The lj speech dataset,” https://keithito.com/LJ-Speech-Dataset/, 2017.

[58] J. Yamagishi, C. Veaux, K. MacDonald et al., “Cst vsctk corpus: English multi-speaker corpus for csr voice cloning toolkit (version 0.92),” 2019.

[59] H. Zou, V. Dang, R. Clark, Y. Zhang, R. J. Weiss, Y. Jia, Z. Chen, and Y. Sun, “Fibre5: A corpus derived from librispeech for text-to-speech,” Proc. Interspeech 2019, pp. 1526–1530, 2019.

[60] J. Lorenzo-Trueba, T. Drugman, J. Latorre, T. Merritt, B. Putrycz, R. Barra-Chicoté, A. Moinet, and V. Aggarwal, “Towards achieving robust universal neural vocoding,” Proc. Interspeech 2019, pp. 181–185, 2019.

[61] Y. Jiao, A. Gabryś, G. Tinchev, B. Putrycz, D. Korzekwa, and V. Klimkov, “Universal neural vocoding with parallel wavenet,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 6044–6048.

[62] 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 The Speaker and Language Recognition Workshop. ISCA, 2018, pp. 195–202.

[63] M. Müller, “Dynamic time warping,” Information retrieval for music and motion, pp. 69–84, 2007.

[64] J. A. Lee, G. Soutar, and J. Louviere, “The best–worst scaling approach: An alternative to schwartz’s values survey,” Journal of personality assessment, vol. 90, no. 4, pp. 335–347, 2008.

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