# ACCENTED TEXT-TO-SPEECH SYNTHESIS WITH A CONDITIONAL VARIATIONAL AUTOENCODER

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# ABSTRACT

Accent plays a significant role in speech communication, influencing understanding capabilities and also conveying a person's identity. This paper introduces a novel and efficient framework for accented Text-to-Speech (TTS) synthesis based on a Conditional Variational Autoencoder. It has the ability to synthesize a selected speaker's speech that is converted to any desired target accent. Our thorough experiments validate the effectiveness of our proposed framework using both objective and subjective evaluations. The results also show remarkable performance in terms of the ability to manipulate accents in the synthesized speech and provide a promising avenue for future accented TTS research.

*Index Terms*— Text-to-Speech, Accent, Conditional Variational Autoencoder, Controllable Speech Synthesis, Accent Conversion

## 1. INTRODUCTION

Accent in speech is a way of speaking a certain language that can be described on phoneme, rhythmic, intonation and structural levels [1]. As part of one's idiolect, accent carries information about a person's background, such as education, region, and mother tongue [1, 2]. As such, disentangling accent from other speaker characteristics that form one's idiolect, such as pitch and vocal tract shape, remains a challenge.

Even though accented TTS has numerous real-world applications, it has not been the main focus of the Text-to-Speech (TTS) field. Incorporating accent into TTS models would allow for more customizability, e.g., a better identity representation of people with speaking disabilities. Moreover, changing the accent of any conversational AI system has the potential to allow specific users to understand its produced speech better. We hypothesize that learning an accent representation as an auxiliary attribute of a TTS system requires fewer data of a particular accent, given that we have data from other accents to supplement, than training an accent-specific system.

In recent years, TTS has seen improvement in performance with the arrival of attention-based deep learning models [3]. Some examples include the well-known Tacotron and Tacotron2 models [4, 5], FastSpeech [6], or FastSpeech2 [7]. In terms of customizability of TTS, research has been done on modelling speakers, styles, or emotions through various auxiliary mechanisms, such as the Global Style Tokens (GST) [8], Variational Autoencoders (VAE) [9], and their modifications like the Gaussian Mixture VAE (GMVAE) [10]. Motivated by the success of VAE, we propose a novel TTS framework based on conditional VAE in this paper, that allows flexible manipulation of accent.

Most of the research on accented speech focuses on foreign accent conversion (FAC) [11, 12, 13], accent identification, and accented automatic speech recognition (ASR) [14]. FAC is a special case of voice conversion (VC), in which an input audio sample is converted into an output audio sample that is modified, e.g., different emotion, speaker identity, or accent. In FAC, the goal is to convert the input L2 (second language speaker) speech into an L1-like (native speaker) speech. Unlike in FAC, our aim is to develop a system capable of generating speech in any accent, for any speaker (no L2 or L1-specific conversion). Moreover, our proposed method is a TTS system, which can generate speech from any text without the need for source audio.

In this work, we propose an efficient and reliable TTS system based on Tacotron2 that utilizes a Conditional Variational Autoencoder (CVAE) [15] to allow accent conditioning while retaining speaker identity. The main objective of the proposed architecture is to synthesize speech in the style of the source speaker converted to a target accent. The contributions of this work are as follows: 1) We present a novel framework for controllable speech synthesis with a focus on accent conversion; 2) The proposed framework allows disentanglement of accent and speaker characteristics; and 3) Converting a speaker's accent is simple and does not require any reference audio.

The rest of the paper is organized as follows: In Section 2 we present the related work, followed by a description of our proposed method. We describe the training procedure and experiments in Section 4, and Section 5 concludes the study.

## 2. RELATED WORK

In speech synthesis, targeting accent is mostly a domain of Foreign Accent Conversion (FAC) frameworks [11, 12, 13]. One such framework is Accentron [11], in which the accent



Fig. 1: An illustration of the training phase and overall architecture of the proposed framework, Tacotron2 with CVAE encoder.

and speaker representations are provided via two pre-trained classifiers to achieve disentanglement. In [13], the disentanglement is achieved through the use of adversarial learning with an auxiliary speaker classifier.

When it comes to controllable speech synthesis in TTS, selected major contributions include GST [8], GMVAE-Tacotron [10], and VAE for speaking style modeling [9]. In GST, a set of tokens is learnt in an unsupervised manner from the input reference audio files and these tokens can learn different attributes in speech, such as pitch, pace, or noisiness of the signal. In [10], the ability of GMVAE to capture different attributes was shown as well. Other work that uses a VAE module to capture different speaking styles is that of [9], where the focus was on latent prosody attributes such as affect and intent. In [16], a Multi-Level VAE is used in an attempt to disentangle speakers and accents. [17]'s interesting work on accented TTS focuses on changing the accent intensity of L2 speakers to make them souns as L1 speakers. This has been done through an accent variance adaptor that modifies phoneme energy, duration, and pitch.

In this paper, we use a Conditional VAE (CVAE) to learn a disentangled representation for speakers and accents to allow accent conversion of any selected speaker to any target accent during synthesis.

## 3. PROPOSED METHOD

The architecture of the proposed method is shown in Fig. 1. It consists of Tacotron2 [5] and Posterior Encoder (Fig. 2). As the Posterior encoder, we have opted to use a CVAE architecture [15] with the objective of maximizing the evidence lower bound (ELBO) of the intractable marginal log-likelihood of data  $\log p_{\theta}(X|\mathbf{y})$ :

$$\log p_{\theta}(X|\mathbf{y}) \ge \mathbb{E}_{q_{\phi}(z|X)}[\log p_{\theta}(X|\mathbf{z}) - \log \frac{q_{\phi}(z|X)}{p_{\theta}(X|\mathbf{y})}] \quad (1)$$

where  $\theta$  and  $\phi$  represents neural networks parameters for decoder and posterior encoder respectively and  $p_{\theta}(X|\mathbf{y})$  denotes a posterior distribution of latent variable  $z = [z_s, z_a]$  with



Fig. 2: Posterior Encoder architecture based on CVAE.

given label condition  $y = [y_s, y_a]$ . The negative ELBO is then used as training loss, which can be viewed as the sum of reconstruction loss  $-\log p_{\theta}(X|\mathbf{z})$  and the KL divergence loss  $\log q_{\phi}(z|X) - p_{\theta}(X|\mathbf{y})$ .

The  $L_2$  loss between predicted mel spectrogram  $\hat{X}$  and ground truth mel spectrogram X is used as reconstruction loss:

$$L_{recon} = ||\hat{X} - X||_2 \tag{2}$$

where  $||.||_2$  denotes  $L_2$  norm. For the CVAE encoder, we propose two variants. The first one follows the traditional CVAE concept of having a label passed as a condition to both its encoder and decoder. The intuition is that the speaker and accent are mainly determined by the provided labels and the latent distribution captures minor differences inside these categories, like prosody. The second variant uses labels only in the encoder. Thus, the whole accent and speaker representation is captured by the latent variables  $z_a$  for accent and  $z_s$  for speaker. We name these two variants CVAE-L, and CVAE-NL, standing for 'label', and 'no-label', respectively.

The generated  $z_a$  and  $z_s$ , each of size 128, are concatenated with the text embeddings and passed through a single linear layer. The output is then passed to the decoder to generate a mel spectrogram, which is converted into audio with a pretrained HiFi-GAN.

## 4. EXPERIMENTS

# 4.1. Dataset and Baselines

In our experiments, we use the L2Arctic dataset [18], which contains 27 hours of recorded speech from 24 speakers with 6 distinct accents – Arabic, Chinese, Hindi, Korean, Spanish, and Vietnamese. Each accent is represented by two female and two male speakers and the data is mostly parallel except for a few missing utterances in some speakers.

For our baseline encoders, we chose to use GST [8] and GMVAE [10], both combined with the same Tacotron2 system. The GST module uses 10 tokens with 8 attention heads to produce an embedding of size 256. As in the original paper, the training is unsupervised. For the GMVAE baseline, we follow the architecture as in [10], but use two observed encoders – one for accent, one for speakers – and no latent encoder. The embedding size is 16 for each encoder and the number of mixtures is 6 for accents and 24 for speakers. As such, this framework uses both the speaker and accent labels as input.

#### 4.2. Training and Inference

We train all models with a batch size of 64 and use ADAM optimizer for 150k steps. The KL loss coefficient is set to  $1 \times 10^{-4}$  at the beginning of training. After reaching 10k steps, it linearly increases to  $5 \times 10^{-4}$  until 35k steps and is kept constant afterwards. All of the models are trained with the target mel spectrogram both as the reference input and target output as well as the relevant text input.

During inference, the model can use reference audio files for speaker and accent modelling. Additionally, with the posterior encoder being a VAE module, we can sample from the distribution to generate the embeddings. For our experiments, we first use the validation set to extract the  $\mu_a$  and  $\mu_s$  values (Fig. 1) for each sample and store them. Then, to represent a specific speaker and a specific accent during inference, we average the stored  $\mu_s$  and  $\mu_a$  values across the respective speaker and accent, leaving us without the need for further reference audio. In our baseline models, we adopted a similar approach of taking the average representation for each accent and speaker during inference.

#### 4.3. Accent and Speaker Modelling Analysis

We visualized the embedding space of the CVAE-NL variant by encoding reference audio of the validation set and performing a t-distributed stochastic neighbor embedding (t-SNE) on 12 of the 24 speakers. In Fig. 3a, we can see that the speaker embeddings clearly form clusters per speaker. In Fig. 3b, we observe overlap between speakers of the same specific accents. Interestingly, the combined (concatenated) embeddings in Fig. 3c show even more compact clusters. This shows that the identity of each speaker is determined by both of the embeddings to a certain degree. One can imagine that if we move



(c) Combined embeddings of  $z_s$  and  $z_a$ .

**Fig. 3**: A t-SNE projection of the CVAE-NL embeddings. Colours represent accents, markers represent speakers.

inside the combined embedding space by changing accent embeddings only, we might get a representation of a different speaker too. Naturally, we have observed this phenomenon in some of the synthesized audio samples with accent conversion, which influenced the design of the subjective evaluation tests, described in Section 4.5.

#### 4.4. Objective Evaluation

We use Mel Cepstral Distortion (MCD) [19] to assess the mel spectrogram reconstruction capability of each model. Word Error Rate (WER) is used to assess the intelligibility of the synthesized speech. For this purpose, we use enterprise-grade speech-to-text pre-trained silero models [20]. The results in Table 1 show that all the models are on par when it comes to MCD and WER. Our proposed methods of CVAE-NL and CVAE-L show a slightly better performance in terms of MCD



(a) MOS results with 95% CI for naturalness without and with accent
 (b) XAB gene (b) XAB gene (c) XAB gene (c

(b) XAB general preference tests of accent-conver	ted au	d10.
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Metric	GT	CVAE-NL	CVAE-L	GMVAE	GST
MCD↓	-	7.10	6.98	7.31	7.25
WER $\downarrow$	0.2082	0.254	0.239	0.254	0.219

 Table 1: Objective Evaluation results (the lower the better).

but fall behind in terms of WER compared to GST. This demonstrates that the proposed method synthesizes state-of-the-art speech quality.

#### 4.5. Subjective Evaluation

We evaluate the performance of the proposed method<sup>1</sup> and baselines via listening tests. A total of 15 participants attended our experiments and each listened to 186 samples. The naturalness of audio is assessed through Mean Opinion Score (MOS) [21]. We note that all frameworks achieve comparable results in terms of naturalness as reported in Fig. 4a. Interestingly, CVAE-NL and GST show better performance after accent conversion, while CVAE-L shows performance degradation in terms of naturalness. These results show that the proposed framework does not suffer much in terms of naturalness when the accent conversion is performed, which is a necessary attribute of the system.

We further assessed the performance of the proposed method in terms of accent and speaker similarity. We note that MOS has been used in both experiments, as we want to quantify the perceived trade-off between accent and speaker identity after conversion. In the accent similarity test, listeners are given two reference samples - one of the source speaker to get an idea about the original accent, and one of the target accents represented by a different speaker. The results (Fig. 4a) show that both of the proposed methods perform better for accent conversion than the baselines, with CVAE-L being the best. On the other hand, GMVAE performed very poorly in this experiment. In the speaker similarity test, the reference sample provided is of the source speaker before conversion. Participants are to judge "how well the original speaker identity is retained after the accent conversion" on a 5-point scale. Fig. 4a shows that the performance of the proposed CVAE-L and CVAE-NL are on par with GST, but lag behind GMVAE. This reflects the trade-off between retaining speaker identity and converting accent as the GMVAE baseline converts accent only very little if at all.

Furthermore, we conducted an XAB [22] preference test to assess general preference of accent-converted audio without specific focus on either accent or speaker identity. In this test, listeners are presented with a reference sample of the source speaker in their original accent and a reference sample of the target accent. For this test, we excluded the GMVAE model since its conversion capability was reported low as shown in the previous results. The results in Fig. 4b show that both of the CVAE variants were preferred over GST. Moreover, CVAE-L seems to be prefered over CVAE-NL. This shows that the proposed CVAE framework is an improvement to the state-of-the-art in accented TTS.

#### 4.6. Discussion on accent-identity balance

The proposed CVAE model achieves promising results in terms of objective and subjective evaluation. As shown in Section 4.3, the embedding space allows for strong accent conversion but this can come at the price of identity disruption. This accent-identity balance is a complex issue, as accent partially forms a person's identity. On this note, the baseline of GMVAE seems to have captured speaker identity too well, hence not allowing for a significant change in accent. In future work, we aim to focus on designing stronger disentanglement mechanisms to better separate accent from speaker identity.

## 5. CONCLUSION

This paper introduces a novel framework for accented TTS, which fuses a Conditional Variational Autoencoder with the Tacotron2 system. The proposed framework allows for efficient synthesis of any chosen speaker's speech converted to any of the target accents. We conducted extensive objective and subjective tests to evaluate the efficacy of the proposed approach. The results show a strong performance in the ability to synthesize natural-sounding speech in a converted accent, which pushes the state-of-the-art boundaries. We discuss the accent-identity balance and sketch out possible improvements in the development of accented TTS.

<sup>&</sup>lt;sup>1</sup>Samples available at https://dapwner.github.io/CVAE-Tacotron/ Code available at https://github.com/Dapwner/CVAE-Tacotron

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