CROSS-LINGUAL TEXT-TO-SPEECH WITH FLOW-BASED VOICE CONVERSION FOR IMPROVED PRONUNCIATION

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ABSTRACT

This paper presents a method for end-to-end cross-lingual text-to-speech (TTS) which aims to preserve the target language’s pronunciation regardless of the original speaker’s language. The model used is based on a non-attentive Tacotron architecture, where the decoder has been replaced with a normalizing flow network conditioned on the speaker identity, allowing both TTS and voice conversion (VC) to be performed by the same model due to the inherent linguistic content and speaker identity disentanglement. When used in a cross-lingual setting, acoustic features are initially produced with a native speaker of the target language and then voice conversion is applied by the same model in order to convert these features to the target speaker’s voice. We verify through objective and subjective evaluations that our method can have benefits compared to baseline cross-lingual synthesis. By including speakers averaging 7.5 minutes of speech, we also present positive results on low-resource scenarios.

Index Terms— cross-lingual text-to-speech, voice conversion, pronunciation preservation, normalizing flows

1. INTRODUCTION

Neural TTS has seen large improvements in terms of acoustic modeling, from attentive Tacotron models \cite{1, 2} to non-attentive \cite{3, 4} and flow-based \cite{5} approaches. As a sub-task, multilingual TTS presents a considerable challenge as native pronunciation plays an important factor on output speech quality. Various approaches can be applied on this task, such as standard TTS architectures \cite{6} or even voice conversion \cite{7}. In such work, we consider a method that can utilize both approaches in a single model using normalizing flows.

1.1. Related work

One of the first approaches on neural multilingual TTS is \cite{6}, in which an adversarial speaker classifier is shown to improve pronunciation during cross-lingual synthesis. Utilizing transformer layers, a similar approach \cite{8} is applied on a larger scale to 50 language locales. In \cite{9}, language-specific text encoders are generated with a meta-learning framework, whereas in \cite{10} cross-lingual word embeddings are used in a Tacotron2-based system.

In many cases, the lack of abundant multilingual data forms a major limitation for neural models. In \cite{11} this problem is alleviated by using voice conversion with HiFiGAN-VC \cite{12} and HiFiGAN \cite{13} in order to create an augmented artificial multilingual dataset for the target speaker. Similarly, a separate cross-lingual voice conversion model using bottleneck feature extraction is trained in \cite{14}.

Voice conversion or cloning techniques can also be directly applied on cross-lingual tasks. Phonetic posteriorgrams (PPGs) are a common feature for efficient voice conversion and are applied successfully on a bilingual setting in \cite{15} and as a linguistic representation for cycle consistency loss in \cite{16}. In \cite{17}, PPGs are replaced with learned linguistic representations, increasing naturalness and speaker similarity. Adversarial training is investigated in \cite{18} for limited data bilingual conversion. In \cite{19}, a voice cloning model is able to utilize latent linguistic embeddings from English data to generalize in other languages with high speaker similarity. S3PRL-VC \cite{20} is an open-source framework that supports cross-lingual voice conversion based on self-supervised representations, reporting successful results on the multilingual tasks of VCC2020 \cite{7}.

Normalizing flows have been recently applied to TTS producing promising results as in Glow-TTS \cite{5} and the state-of-the-art VITS \cite{21}. As shown in \cite{22}, the latter can be efficiently modified for multilingual TTS. YourTTS \cite{23} is also based on the same model and focuses on zero-shot multilingual cloning. While achieving high quality results, in cross-lingual cloning the speaker similarity scores decrease dramatically. GlowVC \cite{24} presents a text-free voice conversion model based on Glow-TTS that performs language-independent cross-lingual voice conversion, presenting results also in unseen languages.

1.2. Proposed method

Voice conversion is shown to be efficiently combined with TTS models, as a data augmentation method \cite{11} or by cascading high quality TTS and post-processing VC modules \cite{25}. In our work, we propose a two-step approach for cross-lingual TTS that relies on a single model trained on multilingual data. We base our model in Glow-TTS \cite{5}, which presents a way to efficiently disentangle speaker and linguistic information, being able to simultaneously perform TTS and VC by conditioning a flow-based decoder on speaker embeddings. The encoder part of our model is based on non-attentive Tacotron \cite{3}, which provides explicit phoneme durations, simplifying the original architecture by not requiring the Monotonic Alignment Search (MAS) algorithm during training. A similar model is used in GlowVC \cite{24} for cross-lingual VC.

Training this model on multilingual data enables a two-step cross-lingual inference method, by first producing speech from a native speaker of the target language and as a second step performing voice conversion to the target speaker. Results indicate that our method has potential benefits on cross-lingual output pronunciation, while on average it improves output intelligibility compared to the baseline. Including speakers averaging 7.5 minutes of speech in the training set, the same model is also shown to operate in the low resource case with a single training process.
2. METHOD

Here we present the model’s architecture and how normalizing flows provide a good solution for the specific task. We also present our proposed method, applying flow-based voice conversion for improving pronunciation in cross-lingual TTS.

2.1. Acoustic model

The model architecture shown in Fig. 1 follows an attention-free approach, based on non-attentive Tacotron [3]. Input phonemes are converted to acoustic features for the LPCNet vocoder [26], which has been shown to produce high quality results in our previous work [27]. In this work, we replace the autoregressive decoder and convolutional post-net with a normalizing flow, based on Glow-TTS [5].

The input text of the given languages is first converted to phonemes by the corresponding frontend module and each phoneme is assigned the language id as a post-fix, so that it becomes unique. That is, we do not use language embeddings as input, but different unique phoneme sets for each language. The phoneme sequences \( p_{\text{lang}} = [p_{\text{lang}}^1, \ldots, p_{\text{lang}}^N] \) are processed by a Tacotron-based CBHG encoder and are converted to linguistic representations \( e = [e_1, \ldots, e_N] \). These representations are upsampled by a Gaussian Upsampler module [8] to frame level vectors \( f = [f_1, \ldots, f_T] \), based on phoneme durations extracted using an external forced alignment module. This module consists of a triphone acoustic model, trained on the same multilingual dataset using the Kaldi toolkit [28]. As a final step, the upsampled sequences are projected by linear layers into frame-level statistics \( \mu = [\mu_1, \ldots, \mu_T], \sigma = [\sigma_1, \ldots, \sigma_T] \) of a Gaussian base distribution, which are matched with the target acoustic features in the maximum likelihood training of the flow-based decoder.

Different speakers in the dataset are modeled by learnable speaker embeddings \( s_{\text{speaker}} \), extracted using a simple lookup table. These embeddings condition the flow-based decoder, as in the original model [5], which is shown to enable both multispeaker synthesis and voice conversion in the same model. The speaker embeddings also condition the duration predictor, after being broadcast-concatenated with the detached phoneme encoder outputs, in order to predict the target phoneme durations during inference time.

2.2. Flow-based decoder

In our model the MAS algorithm introduced in Glow-TTS is not used, since explicit durations are given by the duration predictor. Instead, we can directly model the conditional distribution of acoustic features by transforming the base distribution through the flow-based decoder which is also conditioned on speaker identity, as shown in Equation [1]

\[
\log P_Y(y|p, s) = \sum_{i=1}^{T} \log \mathcal{N}(z_i; \mu_i, \sigma_i) + \log \begin{vmatrix} \frac{\partial f^{-1}_{\text{dec}}(y|s)}{\partial y} \end{vmatrix}
\]

where \( y \) denotes the acoustic features, \( p \) the phoneme sequence and \( s \) the speaker identity. Acoustic features are converted by the decoder into latent values \( z \), which are considered to be samples from the corresponding base distributions. These properties simplify the training goal to simple Maximum Likelihood Estimation (MLE) without requiring additional losses, like mean squared error.

Instead of using the Squeeze usage operated in the Glow architecture, we modify the base statistics projection layers to predict \( r \cdot L \) dimensions, where \( L \) is the acoustic feature dimension and \( r \) is a reduction factor, similar to the original Tacotron model [1]. As these layers follow the Gaussian upsampler, we divide the phoneme durations by \( r \) allowing the model to match this coarser time scale. From prior work [27] we have noticed that for the specific set of acoustic features a reduction factor produces higher quality results.

2.3. Flow-based voice conversion

In the model description we notice that the base distribution statistics \( (\mu, \sigma) \) depend only on the input phonemes and their durations. So during inference, when the latent values \( z \) are sampled, they are independent of speaker identity, which is only considered during their transformation to the output acoustic features. In the multilingual setting, this property not only enables the model to learn speaker-independent acoustic representations for each language, but also to perform voice conversion efficiently between speakers, as shown in similar work [24] as well.

Based on the above, apart from the straightforward cross-lingual inference where a target speaker is selected with input phonemes from a language in which they are not considered native, we propose a two-step approach for the same task. Initially, we produce acoustic features by selecting a native speaker \( s \) of the target language, where it is granted that the output quality will be higher as this is an easier task than cross-lingual TTS. Afterwards, we apply the inverse flow-based decoder transformation \( f^{-1}_{\text{dec}}(y|s) \) in order to find the corresponding latent representations \( z \). Then the forward transformation \( f_{\text{dec}}(z|s) \) is applied, conditioned on the target cross-lingual speaker embedding \( s \), in order to produce the final sequence of acoustic features. The efficiency of this method is based on the ability of the model to adequately disentangle speaker information from the linguistic content and transforming the latter into cross-lingual speech without pronunciation degradation.
3. EXPERIMENTS AND RESULTS

In this section we present the models and data used in our tests, the experimental setup and the evaluation methods we used. Our purpose is to compare our proposed method to the baseline.

For the evaluations, we choose to train a multilingual TTS model, as described in section 2. The trained model can directly perform multilingual and cross-lingual inference by selecting the target speaker and the phoneme set of the desired language. This mode will be referred to as Baseline. We denote the TTS-VC mode as selecting a native speaker of the target language for initial inference and then directly applying flow-based voice conversion for the target speaker. Both modes can generate every combination of speaker and language available in the training set, but specifically for TTS-VC we always select the initial speaker’s gender to be the same as the target speaker’s. We make this convention in order to alleviate any gender information that may have leaked during model training and may result in pitch mismatches.

3.1. Data

To train our models we use 89 US English (us), 107 Korean (ko) and 11 British English (gb) internal speakers. For each of the us and ko languages we have included two speakers (1 male and 1 female) that average about 38.9 hours of speech per speaker, which will be referred to as full data speakers and will be used for inference. In the same manner, we have also added two speakers for each language with 100 utterances each, averaging 7.5 minutes of speech, so as to explore the performance of our model in low-resource cross-lingual scenarios. These speakers will be referred to as limited data and are also included in the training set. In total, our dataset comprises 774 hours of speech in 3 languages, 207 speakers and 223 unique phonemes. Note that we consider both primary and secondary stress, that exist only in us and gb, unlike ko. We treat the occurrence of stress on a phoneme by defining a new phoneme type. The gb language will only be used as target for cross-lingual inference, to evaluate how well the model performs generating language of a different English locale, with additional phonemes and diversified accent.

3.2. Experimental setup

We use 24 kHz audio data and extract 22-dimensional features for training the acoustic model, matching the ones that are used in the LPCNet vocoder. These consist of 20 Bark-scale cepstral coefficients, the pitch period and the pitch correlation.

The encoder of the model maps phoneme sequences into 256-dimensional embeddings and applies the CBHG module. Duration predictor and Gaussian upsample are 2-layered bidirectional LSTMs with 256 neurons in each layer. The flow-based decoder contains 12 flow blocks, each one consisting of activation normalization, invertible convolutions with groups of size 4 and affine coupling Wavenet layers with 192 neurons. The reduction factor we chose is r = 4. Also, we use 64-dimensional speaker embeddings to condition the duration predictor and the decoder.

Model parameters are trained using Adam [29]. Batch size is set to 32, learning rate starts at 10^{-3} linearly decaying to 3 \cdot 10^{-5} in 600K iterations and L2 regularization with \lambda = 10^{-6} is applied.

3.3. Objective evaluation

Since we operate on a multilingual setup, it is common to perform intelligibility tests. For this task we choose to evaluate model performance on a separate test set of 500 utterances for each language code. We use the recent state-of-the-art ASR model Whisper [30], which is trained on a very large amount of multilingual data and is proven to be robust to various accents and noise. In Table 1 we report the results of the tests in Word Error Rates (WER). We note that the ground truth samples that were selected from the same test speakers were not the same as the test set, so in some setups their WER appears higher, but their results are reported in order to verify the validity of the ASR model in our data. For conclusions, we focus on the relative differences between the baseline and proposed setups.

| Target | Full-us | Lim-us | Full-ko | Lim-ko |
|--------|---------|--------|---------|--------|
| us     | 2.89    | 2.87   | 4.25    | 3.07   |
| TTS-VC | 2.92    | 2.83   | 3.89    | 2.90   |
| GT     | 3.32    |        |         |        |
| ko     | 27.86   | 20.81  | 18.48   | 17.78  |
| TTS-VC | 25.94   | 21.49  | 18.15   | 15.74  |
| GT     | 19.84   |        |         |        |
| gb     | 4.41    | 3.72   | 6.27    | 3.96   |
| TTS-VC | 4.10    | 3.21   | 4.81    | 3.92   |
| GT     | 3.01    |        |         |        |

3.4. Subjective evaluation

Our models were assessed via mean opinion score (MOS) listening tests against naturalness, accent and speaker similarity. For US and GB English, evaluations were collected from crowdsourced listeners on Amazon Mechanical Turk [31], in the US, CA (Canada) and GB locales. Every audio sample was evaluated by 10 unique participants. For Korean, 8 native listeners were recruited in our premises.

Listeners were asked to evaluate each sample on a 5-point Likert scale, while listening through headphones and being in a quiet setting. Naturalness was evaluated on a scale from “1: very unnatural” to “5: completely natural”. For accent nativity, listeners were asked to rate on a scale from “1: Very strong foreign accent” to “5: Native accent”. Since most experiments were cross-lingual and no natural sample of the target language was always available for the target speakers, we conducted multispeaker tests (grouped by target language) for naturalness and accent. Speaker similarity evaluation included samples of one target speaker per page and a reference sample. Choices ranged from “1: Sounds like a totally different person” to “5: Sounds like exactly the same person” compared to the reference sample. We used the controls described in [32] to control for potential spurious participants and validate our results. For each target language, 10 phonologically rich test sentences were chosen from conversational corpora and Wikipedia articles via our corpus selection tool [33].

3.5. Results

The results of the subjective evaluation for accent and naturalness are reported in Table 2 and for speaker similarity in Table 3. By applying the controls mentioned in section 3.4 in order to ensure the validity of listener responses, the total number of ratings is further reduced, making the confidence intervals larger. By observing the final tables, the overall differences of multiple experiments are small and results are not statistically significant. However, if we also take into account the difficulty of the subjective evaluation task between similar system setups, we can observe some clear tendencies.

In accent evaluation experiments, we observe that the TTS-VC method performs better on average compared to the baseline on full data speakers. The largest differences are noted on ko speakers when the target languages are us and gb. For this speaker category,
TTS-VC also slightly improves all same language results, although the source and target speaker during voice conversion is the same. We cannot attribute this improvement to a specific property of our model, so we can hypothesize that the two-step approach can also act as a refinement step of the final result. In the limited data setup, TTS-VC presents improvements only for ko speakers, with this result persisting in both same and cross-lingual inference. Limited data speakers consist of recordings in different environments, as in most real-life scenarios, so these differences may affect the results of this setup. Based on this, we can conclude that as a method, TTS-VC retains some accent properties of the target language and can overall help improve the desired accent. However, for limited data scenarios, different speaker properties and recording conditions are an important factor and in future work more diverse experiments can provide a clearer result.

Naturalness experiments present mixed results. In the majority of experimental setups, the TTS-VC presents higher naturalness on average. This result is mostly consistent on limited data speakers, but with a clear trend also for full data speakers in us and ko cross-lingual inference. For gb the results are mixed, but since this is a naturalness test we conclude that the overall capability of the model for this particular language is reduced to the mid-range (neither natural or unnatural). The training set contains 11 gb speakers, a significantly lower amount than the other two languages, so the model does not perform as well.

For speaker similarity, we have also included the native speaker which acts as the source for the voice conversion process as control in the test pages. The very low ratings of this variable indicate that the target speaker is not similar to the source speaker, thus the voice conversion is successful. Notably, the model yields the lowest performance on the same language limited data ko inference, in which the speaker similarity is low on both model setups. Overall, the results of speaker similarity are mixed, indicating the models are close regarding their capacity to model speaker identities.

In the intelligibility evaluation, TTS-VC on most cases shows improvements on both same language and cross-lingual TTS. Differences on some cases are small, but overall we can conclude that synthesizing with a native speaker produces more intelligible speech in the target language and when the speaker identity is subsequently converted, there is little to no loss of phonetic information, thus resulting in improved WER.

As a final note, we performed these evaluations without regarding the target speaker prosody. One could argue that as voice conversion is performed on another speaker’s synthetic speech, the target speaker style would not be present, as voice conversion would only change the speaker identity and not the content of the sentence. By evaluating the results of our experiments we believe this is true in our setup, as there is no consistent method of evaluating each specific speaker style. While this is a difficult task to resolve in a multispeaker multilingual setting, we also believe that this is the reason our method yields more natural accent on average. The model’s ability to disentangle content and speaker identities enable it to copy the language-dependent prosody and make the final processed speech sound more native in the majority of the cases.

We strongly encourage the readers to also listen to the samples at our website: https://innoetics.github.io/publications/glow-cross-lingual/index.html

Table 2. Subjective evaluation of accent and naturalness (MOS with 95% confidence interval).

| Target | Accent | Naturalness |
|--------|--------|-------------|
|        | Full-us | Lim-us | Full-kro | Lim-kro | Full-us | Lim-us | Full-kro | Lim-kro |
| us     | 4.16±0.13 | 4.31±0.14 | 3.06±0.15 | 4.01±0.14 | 3.99±0.19 | 3.73±0.23 | 3.51±0.21 | 3.53±0.22 |
|        | 4.18±0.14 | 4.17±0.16 | 5.53±0.16 | 4.14±0.14 | 3.74±0.19 | 3.76±0.20 | 3.59±0.22 | 3.68±0.22 |
| TTS-VC | 4.87±0.07 | 4.89±0.06 | 4.54±0.13 | 4.58±0.13 | 3.18±0.33 | 3.90±0.26 | 4.29±0.26 | 4.12±0.27 |
| GT     | 2.95±0.28 | 4.24±0.26 | 4.64±0.16 | 4.23±0.24 | 3.38±0.33 | 4.24±0.30 | 4.28±0.28 | 4.39±0.26 |
| ko     | 3.09±0.28 | 4.22±0.25 | 4.72±0.16 | 4.44±0.23 | 3.32±0.22 | 3.13±0.25 | 2.84±0.28 | 2.99±0.24 |
|        | 3.64±0.16 | 3.67±0.14 | 2.62±0.18 | 3.22±0.17 | 3.10±0.22 | 3.30±0.22 | 2.80±0.28 | 2.99±0.22 |
| TTS-VC | 3.66±0.17 | 3.49±0.17 | 2.89±0.16 | 3.35±0.18 | 4.72±0.07 | 4.72±0.07 | 4.72±0.07 | 4.72±0.07 |
| GB     | 3.66±0.17 | 3.49±0.17 | 2.89±0.16 | 3.35±0.18 | 4.72±0.07 | 4.72±0.07 | 4.72±0.07 | 4.72±0.07 |

Table 3. Subjective evaluation of speaker similarity (MOS with 95% confidence interval).

| Target | Full-us | Lim-us | Full-kro | Lim-kro |
|--------|--------|--------|----------|--------|
|        |        |        |          |        |
| us     | 4.00±0.27 | 4.17±0.31 | 4.33±0.25 | 3.20±0.38 |
| TTS-VC | 3.65±0.39 | 4.22±0.32 | 4.03±0.25 | 3.11±0.40 |
| Control| 1.38±0.34 | 1.38±0.34 | 1.38±0.34 | 1.11±0.21 |
| ko     | 3.32±0.33 | 2.83±0.32 | 4.06±0.30 | 1.71±0.23 |
| TTS-VC | 3.33±0.34 | 2.70±0.35 | 4.04±0.38 | 1.82±0.27 |
| Control| 1.00±0.00 | 1.10±0.19 | 1.00±0.00 | 1.00±0.00 |
| gb     | 2.69±0.23 | 2.88±0.34 | 2.68±0.23 | 2.16±0.27 |
| TTS-VC | 2.66±0.22 | 3.04±0.30 | 2.66±0.26 | 2.24±0.29 |
| Control| 1.29±0.24 | 1.20±0.25 | 1.10±0.19 | 1.00±0.00 |

4. CONCLUSIONS

We have presented a two-step approach for cross-lingual TTS, by combining the speech synthesis and voice conversion capabilities of a flow-based model. Training of a single model is performed on multilingual data, including low resource speakers. Subjective results indicate that on average this method can preserve more efficiently the target language pronunciation compared to the baseline, while also being adequately natural, considering the difficulty of the cross-lingual task, especially in the low resource case. Speaker similarity results are close to the baseline, indicating an adequate preservation of target speaker identity, while intelligibility tests present improvements on WER for the majority of cases. As future work, a dataset with more diversified speakers and more languages will be introduced and focus will be given on recording condition and speaker style disentanglement, so that the output quality is increased and the model will also be able to perform unseen speaker adaptation.
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