USING IPA-BASED TACOTRON FOR DATA EFFICIENT CROSS-LINGUAL SPEAKER ADAPTATION AND PRONUNCIATION ENHANCEMENT

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ABSTRACT

Recent neural Text-to-Speech (TTS) models have been shown to perform very well when enough data is available. However, fine-tuning them for new speakers or languages is not straightforward in a low-resource setup. In this paper, we show that by applying minor modifications to a Tacotron model, one can transfer an existing TTS model for new speakers from the same or a different language using only 20 minutes of data. For this purpose, we first introduce a base multi-lingual Tacotron with language-agnostic input, then demonstrate how transfer learning is done for different scenarios of speaker adaptation without exploiting any pre-trained speaker encoder or code-switching technique. We evaluate the transferred model in both subjective and objective ways.

Index Terms— TTS, multilingual, transfer learning

1. INTRODUCTION

Recent TTS models [1], [2], [3] can generate intelligible and high-fidelity speech when trained on tens of hours of speech corpus. However, training them with only a small amount of data results in an unstable TTS model. Different techniques have been proposed for pre-training parts of a TTS model as a pre-training step and then fine-tuning it towards new speakers [4]. In such a case, however, the distinction between the pre-training and the main training phases of the model makes overall convergence more difficult.

The goal of one type of transfer learning in TTS systems called speaker adaption is to adapt an existing model to a new speaker with a limited amount of data. A common way to do speaker adaption is by using a separate speaker encoder and conditioning the speech synthesis on the speaker embedding generated by the speaker encoder. This allows the model to infer the speaker identity from the speaker embedding and makes it possible to extend speech synthesis to unseen speakers during inference [5], [6]. One drawback of such models is their dependency on large multi-speaker datasets for training the base TTS model. Further, it requires a comprehensive speaker embedder to learn as many voice characteristics as possible during training.

Another way of speaker adaption is based on fine-tuning the weights of an already trained model [7], [8]. Assuming the text encoder part of the TTS model has learned “good enough” representations, one usually freezes parts of the model that are supposed to stay fixed and only fine-tunes the remaining parts corresponding to the speaker identity to adapt to the new speaker. As the focus in speaker adaptation has been mainly on monolingual transfer, usually, the text encoder is specific to one particular language and therefore can not be used for transfer learning to a new language. In [9] the authors learn a mapping between the source and target language phoneme, which helps with language transfer; however, one needs a pre-trained ASR model to learn this mapping in an unsupervised manner.

Thanks to large, publicly available datasets, training a single-speaking TTS model in a single language like English can be seen as a straightforward task. However, the open question is if it would be possible to adapt a TTS model to a new speaker from a different language without needing an additional ASR model or speaker embedder. To answer this question, one needs to design the model such that it can accept inputs from the source and target languages at the same time without additional input modules or phoneme converters.

In this work, inspired by the idea of ”learning without forgetting” [10], we look at speaker adaptation from a model weight fine-tuning perspective by preserving the previous speaker(s) in several scenarios. We first introduce a framework based on Tacotron 2 [11] and enhance it with minor adaptations, which make the convergence of the model faster and more stable, especially for cross-lingual cases. The model receives IPA characters as direct input passed through a trainable lookup table for almost all IPA characters, which allows us to easily extend to a new language without using a different encoder per language or any language switching technique. Moreover, we investigate whether fine-tuning a model for a new speaker in a different language with preserving the old speaker(s) characteristics would help the old speaker(s) to speak in the new language intelligibly. Simply put, the main advantages of such a TTS system are:

- Adapting to new speakers in a low-resource setup (from the same or a different language).
- Enabling the source speaker to speak the target language intelligibly and vice-versa.

IPA: https://www.internationalphoneticassociation.org
Learnable Lookup Table
Phone Embedding

NePhoneme N
Phoneme 4
Phoneme 3
Phoneme 2
Phoneme 1

IPA embedding of the source language to the target language

This allows us to easily extend an existing model to a new
subset of the table tensors depending on the source language.

embedding vectors. Each source speaker may use a different
speaker lookup weights respectively.

We will use these parameters to explain the transfer learning
scenarios in the following sections. Similar to Tacotron 2, we
train the model by minimizing the loss term below in both
pretraining and transfer learning steps:

\[ \mathcal{L} = ||Y - Y_{post}||^2 + ||Y - Y_{pre}||^2 \] (1)

where \( Y_{pre} \) and \( Y_{post} \) are the outputs of the decoder’s linear
projection and Post-Net respectively.

For cross-lingual speaker adaptation, we propose a 2-step
inference mechanism which we call Expert Alignment. In ex-
pert alignment, as shown in Figure 2, first we compute the
alignment for a speaker of a different language. We found this to be helpful for cross-lingual transfer with
noisy datasets.

3. TRANSFER LEARNING SCENARIOS

A naive way of fine-tuning is to initialize the network weights
for a new speaker with the optimal parameters obtained from
training on a (single-speaker) large source dataset. How-
ever, once the number of sources and target speakers is dif-
ferent, we cannot just copy the weights from the source
model. Moreover, even in the case of single-to-single speaker
adaptation, simple fine-tuning will result in forgetting the
source speaker, which doesn’t allow us to improve the source
speaker’s pronunciation in the target language. Therefore, we
keep both the origin speaker and add the target speaker(s) in
our setup. In our experiments, we use 20 minutes of data per
speaker. You can listen to demo examples from here.

3.1. Mono-Lingual Speaker Adaptation

In monolingual speaker adaptation, we assume that the text
encoder can already extract proper textual embedding from

2. FRAMEWORK

In this section, we introduce the TTS model that we’ve used
in the experiments throughout this paper.

2.1. Model Architecture

The framework is based on an attention-based sequence-to-
sequence model based on Tacotron’s architecture. The main
modules of the model are an encoder (text encoder) and de-
coder with an attention layer in between, a speaker embed-
ding lookup table, and a phoneme embedding lookup table.

The only change that we made to the original Tacotron model
is adding a residual connection from the input layer to the en-
coder’s outputs, similar to [11]. We found that adding this
residual connection helps with the robustness of the model
during training and inference and causes faster convergence
in the monolingual transfer learning scenario where the en-
coder is frozen.

The input text is first normalized and converted to IPA
phonemes; then, using a lookup table, each IPA character
is converted to an n-dimensional vector. The text encoder,
which consists of a number of convolutional layers and a re-
current layer (in our case, a bi-directional LSTM) on top, con-
verts the input characters to sequence text embedding vectors.

The speaker embedding extracted from the speaker embed-
ding lookup table is then concatenated with the encoder’s out-
puts. The decoder attends over the encoder’s output to gen-
erate the Mel-spectrogram frames of the synthesized speech.

We use Forward attention [12] in the attention layer of our
model. In Figure 1, we show the overall architecture of the
model.

Since the phoneme lookup table is supposed to be uni-
versal, it uses a fixed-size table containing all IPA character
embedding vectors. Each source speaker may use a different
subset of the table tensors depending on the source language.
This allows us to easily extend an existing model to a new
speaker of a different language by transferring the learned
IPA embedding of the source language to the target language
while allowing the model mainly to focus on the new charac-
ters that were not present in the source language.

2.1.1. Training and Inference

In simple words, training a TTS model is done by max-
imizing \( P(Y|X; W) \) where \( X \) and \( Y \) are the input tran-
script and mel-spectrogram of the synthesized speech re-
spectively. In our TTS model, we can expand the term as
\( P(Y|X, S_{id}; [W_e, W_d, W_p, W_s]) \) where \( S_{id} \) is the id(s) of the
source speaker(s) and \( W_e, W_d, W_p, W_s \) are the param-
eters of the encoder, decoder, phoneme lookup weights ad
speaker lookup weights respectively.

First, we train a model on a single or multi-speaker dataset
for a data-rich language. Once the model is fully converged
on the source language, we have optimized weights of the dif-
ferent parts of the model indicated by \( W^e, W^d, W^p, W^s \).
We will use these parameters to explain the transfer learning
scenarios in the following sections. Similar to Tacotron 2, we
train the model by minimizing the loss term below in both
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https://d872c.github.io/ICASSP-2021_TTS
the input text. First, we froze different parts but noticed that both freezing and unfreezing the encoder and phoneme table resulted in almost the same performance. Nevertheless, since freezing keeps the encoder stable for noisy data, we kept the encoder frozen. In Figure 4(a), we show the Mel-cepstral distortion (MCD) of the training data in a monolingual transfer example for a model with and without encoder freezing. We did all monolingual transfer experiments with the objective below:

$$\max P(Y|X, [S_{old}, S_{new}]; [W^e, W^d, W^d, W^s])$$  \tag{2}$$

where the bold elements are frozen during transfer learning, and the rest of the parameters are updated. $S_{new}$ and $S_{old}$ correspond to the old and new speaker IDs, respectively.

3.2. Cross-Lingual Speaker Adaptation

In cross-lingual transfer learning, the target speaker is supposed to be from a different language than the source speaker. Since the target language might use a different combination of phonemes for word pronunciation, freezing the text encoder would cause pronunciation issues in the target language. For the speaker embeddings, similar to the mono-lingual case, we freeze the speaker embedding vector(s) for the old speaker(s) and only let the new speaker(s) adapt their embedding(s) to the TTS model. Therefore we use the objective below to do transfer learning for speaker(s) for a new language.

$$\max P(Y|X, [S_{old}, S_{new}]; [W^e, W^d, W^d, W^s])$$  \tag{3}$$

where the part written in bold is partially frozen.

4. EXPERIMENT SETUP

In this section, we explain the setup for different experiments that we did to evaluate the transferability of our TTS model.

4.1. Datasets

We used single-speaker datasets to train our base model; however, one could also use multi-speaker datasets for this purpose. For the English source model, we used LJSpeech\cite{13}, and for the German source model, we used our internal datasets, which contain one male and one female speaker that we will refer to as Inter-Male/Female. For the rest of the languages like Spanish, French, and Korean, we used CSS10\cite{14} which is publicly available.

For the transfer learning (speaker adaptation) part, we used two random speakers of VCTK and created a 20-min long noisy (imperfect-alignment) dataset from one of Donald Trump’s speeches for the English language. For the German language, also we used 20-min long Angela Merkel’s voice.

4.2. Baseline Model

We used the publicly available source code for Tacotron 2 from NVidia\cite{16} as a baseline. We extended it with a residual connection as described in the Model Architecture section. For text-to-phoneme conversion, we used eSpeak NG\cite{17} phonemizer which supports most languages. We trained each source model with batch-size 80 on a V100 GPU for almost 60K iterations.

4.3. Evaluation Metrics

We use both subjective and objective metrics for the evaluation of the transferred model. To evaluate the intelligibility of the generated sentences in terms of word pronunciation correctness fed the synthesized speech to a pre-trained ASR model based on DeepSpeech\cite{3}. Then, we computed the WER and MER\cite{4} for the ASR model’s output, the original file, and the generated speech from a model in one of the transfer learning models. We also computed the MCD of the training data during the transfer learning as explained in \cite{16}.

The subjective evaluation was only done for the monolingual transfer case for English and German languages. We evaluated 20 different sentences for our three different speakers in both languages using the Amazon Mechanical Turk service. We used the interface and analysis tools provided by\cite{17} to acquire mean opinion scores (MOS) for our audio samples. A total of 117 workers participated in the evaluation, 48 of which were rejected due to misclassifications of our gold standard (trapping) clips, resulting in 20 workers for German 49 for English.

5. RESULTS

5.1. Mono-Lingual Single Speaker Adaptation

In mono-lingual adaptation, we transferred an English source model trained on LJSpeech to two speakers of VCTK and Trump’s voice. The German source model trained on either InterMale or InterFemale was transferred as shown in Table

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3Tacotron 2 - NVidia: https://github.com/NVIDIA/DeepLearningExamples
4eSpeak NG: https://github.com/espeak-ng/espeak-ng
5DeepSpeech: https://github.com/Jaco-Assistant/deepspeech-polyglot
Table 1. Mono-Lingual Transfer

| Mode          | Iters | MCD   | WER | MOS |
|---------------|-------|-------|-----|-----|
| LJ-to-VCTK298 | 3K    | ≈24.0 | 0.56| 3.91|
| LJ-to-VCTK283 | 3K    | ≈23.0 | 0.59| 3.55|
| LJ-to-Trump   | 3K    | ≈23.0 | 0.50| 2.15|
| Male-to-Female| 3K    | ≈22.0 | 0.16| 3.85|
| Female-to-Male| 3K    | ≈25.0 | 0.14| 3.19|
| Male-to-Merkel| 4K    | ≈21.0 | 0.25| 3.68|

Table 2. Cross-Lingual Speaker Adaptation

| Mode      | Iters | MCD   | WER | MER |
|-----------|-------|-------|-----|-----|
| EN2FR     | 7K    | ≈23.0 | 0.58| 0.49|
| EN2DE     | 8K    | ≈20.5 | 0.12| 0.12|
| EN2KO     | 6K    | ≈24.0 | 0.70| 0.64|
| EN2ES     | 5K    | ≈21.5 | 0.10| 0.10|
| KO2FR     | 4K    | ≈25.0 | 0.55| 0.52|
| KO2EN     | 3K    | ≈28.0 | 0.78| 0.77|
| KO2DE     | 19K   | ≈21.0 | 0.24| 0.23|
| KO2ES     | 3K    | ≈25.5 | 0.19| 0.18|
| ES2FR     | 4K    | ≈23.0 | 0.50| 0.44|
| ES2EN     | 10K   | ≈20.0 | 0.25| 0.23|
| ES2DE     | 6K    | ≈21.5 | 0.19| 0.15|
| ES2KO     | 14K   | ≈21.0 | 0.88| 0.78|

Table 3. Cumulative Speaker Adaptation.

| Mode      | Iters | MCD     | WER   | MER   |
|-----------|-------|---------|-------|-------|
| DE2ES2FR  | 3K    | ≈24.5   | 0.61/0.71 | 0.55/0.69 |
| ES2KO2DE  | 7K    | ≈24.0   | 0.19/0.44 | 0.19/0.39 |

5.2. Cross-Lingual Speaker Adaptation

For cross-lingual adaptation, we used LJSpeech and Inter-Male for the English and German source models, respectively, and the single speaker datasets from CSS10 for the rest of the languages. In Table 2, we show the results for adaptation from English, Korean, and Spanish to four different speakers in different languages. The scores are computed for the target speaker in the target language.

We also tested the source speaker’s pronunciation in the target language by sentences whose phonemization had low overlap with the target language. In Figure 4(b), as an example, we show how the attention for the Spanish speaker fails over an English sentence in the top row, and below, we show the attention after ES2EN speaker adaptation.

5.3. Cumulative Cross-Lingual Speaker Adaptation

Another interesting scenario to consider is Cumulative language learning. The goal is to check whether the TTS model can be trained in a cumulative way of cross-lingual learning. For example, given a source model originally trained on English then adapted to a Spanish speaker, would it be able to learn a third and fourth language?

We propose simple modifications and fine-tuning techniques for Tacotron 2 in cross-lingual low-resource speaker adaptation setups. We show that by adopting a universal input definition and speaker embedding, it is possible to adapt to new speakers in a different language from a pre-trained model with a limited amount of data. We also conduct experiments and demonstrate that such adaptations result in better pronunciation of words in the target language for the source speaker and can be generalized to more languages in a cumulative manner.
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