Applying Feature Underspecified Lexicon Phonological Features in Multilingual Text-to-Speech

Cong Zhang¹, Huinan Zeng², Huang Liu³, Jiewen Zheng³

¹ Centre for Language Studies, Radboud University, Nijmegen, Netherlands;
² Faculty of Linguistics, Philology and Phonetics, University of Oxford, Oxford, UK;
³ Shengrenxin Ltd., Beijing, China

cong.zhang@ru.nl, huinan.zeng@ling-phil.ox.ac.uk, huangliu@soundx.cn, martinzheng@soundx.cn

Abstract

This study investigates whether the phonological features derived from the Featurally Underspecified Lexicon model can be applied in text-to-speech systems to generate native and non-native speech in English and Mandarin. We present a mapping of ARPABET/pinyin to SAMPA/SAMPA-SC and then to phonological features. This mapping was tested for whether it could lead to the successful generation of native, non-native, and code-switched speech in the two languages. We ran two experiments, one with a small dataset and one with a larger dataset. The results supported that phonological features could be used as a feasible input system for languages in or not in the train data, although further investigation is needed to improve model performance. The results lend support to FUL by presenting successfully synthesised output, and by having the output carrying a source-language accent when synthesising a language not in the training data. The TTS process stimulated human second language acquisition process and thus also confirm FUL’s ability to account for acquisition.

Index Terms: phonological feature, FUL model, text-to-speech, multilingual TTS, non-native speech

1. Introduction

Many latest modelling experiments in text-to-speech (TTS) or commercial TTS systems adopt language-specific phone labels such as ARPABET (a.k.a. CMU phones) for English, and pinyin for Mandarin Chinese. However, despite their high performance, each individual language requires a different phone set. When training models for any new or additional language, the front-end system often has to alter extensively to suit the input of the new or additional language. The changes bring extra workload and delay the development progress whenever a new language is added. To optimise the workflow, a more universal input representation is needed for as many languages as possible. Therefore, we propose an input system based on phonological feature theories with an aim to progress towards a universal TTS system. The benefits of using phonological features rather than language-specific labels, or the more universal IPA are that: (1) a much smaller and limited number of features are used to represent all languages. Even though IPA is already a smaller set of labels than merging language-specific labels from different languages, it is still expandable based on the languages and would result in more than 60 labels. Phonological features amount to a much smaller number. For instance, the current study proposes a set of 19 phonological features in total. (2) A unified feature set for multiple languages means being able to pool data from different languages together and therefore reducing the amount of data needed for model training, as well as solving the data sparsity issue. This is especially beneficial for under-resourced languages which have a limited amount of available data or well-defined input labels. (3) It fuses multiple languages across speakers into a unified acoustic model, making the deployment for production much easier. One specific instance is that when generating code-switch speech, the timbre would be the same in different languages.

Previous works have investigated the possibility of applying phonological features in TTS [1]–[4]. [1]'s models were trained with an English corpus and a Mexican Spanish corpus using ten non-theory-driven phonological features, and successfully synthesised German speech, which was not present in the training data. [2] examined three sets of phonological features and their combined uses: PHOIBLE [5], PanPhon [6], and PhonClassCounts [7]. The numbers of features for the three sets were 37, 23, and 13 respectively. [2] trained their models on a nine-language dataset that contained both Indo-Aryan and Dravidian languages. Three out of the five test languages (one in training data, two not) showed advantages over the phonemic baseline model. They ascribed the two unsuccessful languages (one in training data, one not) to the suboptimal design for the phoneme inventories. The MOS in the models using phonological features ranged from 2.53 to 3.85 in their experiment. [3] used a set of 23 phonological features based on articulatory-inspired IPA (International Phonetic Alphabet) definitions. They trained models with subsets of a six-language corpus (666.8 hours). Their results showed that the models yield the highest MOS (3.68) when the test language (English) is typologically similar to the train languages (German + Spanish), while the lowest score (1.70) was for the typologically more distant languages between the train (Spanish and Korean) and the test (French) languages. [4] used 19 SPE features [8] and five text-based features. Their models were trained on English and/or German data, and the test language was German. Their results showed that when the training data contained 14 hours of English and 15 minutes of German, the final results showed comparable naturalness to the models trained on four hours of German, using either phonemes or phonological features.

The major success achieved by the previous studies was mainly among typologically similar languages. In this study, we examine two typologically distant languages, Mandarin and English. Moreover, the lexical tone specification in Mandarin and the lack of it in English presented an extra dimension of difficulty. The current study also differentiates from past studies in that it is based on a well-examined theoretically driven phonological model, Featurally Underspecified Lexicon (FUL) model [9], [10], following its
successful application in an automatic speech recognition (ASR) system [11]. FUL has also been tested extensively in human speech perception [12] and production [13], as well as child [14] and L2 language acquisition [15].

The goals of this paper are not to provide a better TTS modelling technique, but to 1) test whether FUL theory can be supported by speech synthesis models; 2) further test the feasibility of applying phonological features in multilingual TTS; and 3) present a mapping between the widely adopted phone symbols (English: ARPABET; Mandarin: pinyin), and their mapping with FUL features, via intermediate coding systems (English: SAMPA [16]; Mandarin: SAMPA-SC [17]). The mapping has been made publicly available through https://zenodo.org/record/5553685 [18]. This direct mapping makes the results from this study directly applicable to existing TTS systems which take ARPABET and pinyin as input and already have a substantial amount of labelled data.

2. Theoretical Background

2.1. Featurally Underspecified Lexicon (FUL) Features

![Figure 1: Feature organisation in the FUL model][20]

Distinctive features, first proposed by [19], are designed to describe the phonological systems in the world’s languages. It has received continuous attention among phonologists since its birth. Different feature organisations have been proposed (see [10] for a review). Figure 1 shows the FUL feature geometry. There is only a handful of features in this system. The manner of articulation is represented by the root features, constriction features, and [strident, nasal, lateral, rhotic]. Laryngeal features mark the voice of articulation and the place of articulation is indicated by the place features. The FUL model is used for the following reasons: (1) All features are monovalent and there are no dependent features. Comparing with the systems where there are binary features and feature dependencies, FUL’s feature marking is more straightforward. Monovalent keeps the dimensionality of the final input vector to a minimum. (2) Consonants and vowels share place features. No extra feature is needed to describe vowels. For example, labial consonants and rounded vowels are [labial], coronal consonants and front vowels are [coronal], and dorsal consonants and back vowels are [dorsal]. For consonants, the tongue height and tongue root features become relevant when there are contrasts within the same articulator. For instance, contrasts within coronal sounds e.g., dental, palatals vs. retroflexes, can be established by a combination of [coronal] and tongue height features. The number of features is therefore also kept to a minimum. (3) The features in the geometry have acoustic correlates, e.g., the tongue height feature [high] is characterised by the concentration of more energy at higher frequencies and a low F1, and vice versa for the feature [low].

2.2. Feature sets for Mandarin and English

2.2.1. English

The features for the phonemes in General American English in this study are shown in Table 1. The parentheses indicate that the feature specification for the phone is optional as it is not required to establish contrast within the language, but it is specified in this study since our aim is to build a cross-linguistic system which can distinguish both English and Mandarin. There are 38 phonemes, within which 24 are [consonantal] and 14 are [vocalic]. Consonants are further divided up by the root features [obstruent] and [sonorant], the affricates /ʤ ʧ/ also being [strident]. All sonorant consonants are specified for [voice], [continuant], [continuant], [plosive], [plosive], [plosive].

Obstruents contrast in voice. Voiced obstruents /b v d đ dʒ d z ɡ y/ are specified for [voice] and voiceless obstruents /p t ɡ f ð θ s z ʃ ʒ h/ are not specified for laryngeal features. The plosives, fricatives, and affricates are distinguished by the feature [strident] and the constriction features [plosive] and [continuant]. Plosives /p b d t g k/ are [plosive]. Fricatives /f ɦ th s z ʃ ʒ h/ are [continuant], with /s z ʃ/ also being [strident]. Affricates /ʤ ʧ g/ are [plosive, strident].

General American English also makes use of the tongue root features to establish the tense /u o i e ʌ/ and lax vowel /ʊ ɔ ɪ ɛ ə ɚ ɝ ʌ/ not specified for tongue height. General American English also makes use of the tongue root features to establish the tense /u o i e ʌ/ and lax vowel /ʊ ɔ ɪ ɛ ə ɚ ɝ ʌ/ are not specified for tongue height.

The true diphthongs in General American English are [e i o ʌ ə ɛ ɪ ʊ ɔ ɹ ɡ ɥ ɝ]. There are two [hiotic] vowels /e i/.

| Features          | English phonemes |
|-------------------|------------------|
| CONSONANTAL       | b v f d t ɡ j dʒ d z ɡ y |
| VOCALIC           | u o i e ʌ |
| SONORANT          | m n ŋ w j |
| OBSTRUENT         | p v f d t ɡ j dʒ d z ɡ y |
| VOICE             | b v f d t ɡ j dʒ d z ɡ y |
| SPREAD GLOTTIS    | p v f d t ɡ j dʒ d z ɡ y |
| PLOSIVE           | v f ɡ j dʒ |
| DORSAL            | b v f d t ɡ j dʒ d z ɡ y |
| LABIAL            | b v f d t ɡ j dʒ d z ɡ y |
| CORONAL           | b v f d t ɡ j dʒ d z ɡ y |
| HIGH              | i o i e ʌ |
| LOW               | ɡ j dʒ d z ɡ y |
| ATR               | u o i e ʌ |
| RTR               | ɡ j dʒ d z ɡ y |
| NASAL             | m n ŋ w j |
| LATERAL           | b v f d t ɡ j dʒ d z ɡ y |

Figure 1: Feature organisation in the FUL model [20]

Table 1: Features for English phonemes
Table 2 shows the features of the 37 Mandarin phonemes. 21 phonemes are [CONSONANTAL] and 16 phonemes that are [VOCALIC]. The overall number of sounds, as well as the number of vowels and consonants, are similar to that of General American English. Different from English, Mandarin obstruents contrast in aspiration instead of voicing. The aspirated obstruents /pʰ tʰ sʰ tsʰ tɕʰ kʰ/ are specified for [SPREAD GLOTTIS] and the unaspirated ones [p t s ts tɕ tɕʰ] are not specified for LARYNGEAL features. The only voiced obstruent /ʐ/ is analysed as a syllabic approximant ([ʐ]) or an apical vowel ([ɻ]) in other studies. This study follows [21] and treat it as /ɻ/ [CONSONANTAL, OBSTRUENT, VOICE]. Mandarin has a three-way coronal contrast – dental [s ts tsʰ] vs. alveolo-palatal [ɕ tɕ tɕʰ] vs. retroflex [ʂ ʈʂ ʈʂʰ]. The alveolo-palatals and dentals are in complementary distribution. The dentals are the phonemes /s ts tsʰ/ and the alveolo-palatals are the surface allophones [ɕ tɕ tɕʰ]. The phonemes realise as [ɕ tɕ tɕʰ] when they occur before the high front vowels /i y/ and as [s ts tsʰ] in other phonological environments. The dental and retroflex phonemes are distinguished by the TONGUE HEIGHT features. The retroflexes are marked as [RTR] and the dentals are not specified for TONGUE HEIGHT. The Mandarin sonorant consonants /m n ŋ j l/ have the same features as those in English. Mandarin does not have [RHOTIC] consonants. Mandarin has a larger number of nasalised vowels and thoric vowels than English. [ɐ ɑ ɐ̃ ɔ ə] are [RHOTIC] and [ɹ ɹ̃] are [NASAL, RHOTIC]. Besides the back rounded vowels that also exist in English, Mandarin has a front rounded vowel /ɻ/ [LABIAL, CORONAL].

| Features            | Mandarin phonemes                     |
|---------------------|---------------------------------------|
| CONSONANTAL         | [p pʰ t tʰ s sʰ ts tsʰ tɕ tɕʰ k kʰ]  |
| VOCALIC             | [i u ũ ʊ o ɔ e ɛ ɛ̃ a ã _duplicate]  |
| SONORANT            | [m n ŋ j l ŋ u ũ u˞ u ũ̃ ũ̃]         |
| OBSTRUENT           | [p pʰ t tʰ s sʰ ts tsʰ tɕ tɕʰ k kʰ]  |
| VOICE               | [z m n ŋ j l ŋ i y u ũ u˞ u ũ̃]       |
| SPREAD GLOTTIS      | [pʰ tʰ sʰ tɕʰ]                        |
| PLOSIVE             | [pʰ tʰ s sʰ ts tsʰ tɕ tɕʰ k kʰ]       |
| CONTINUANT          | [ʃ s ʃ sʰ]                           |
| LABIAL              | [pʰ f m w y u ũ u˞ u ũ̃]             |
| CORONAL             | [tʰ s sʰ ts tsʰ tɕ tɕʰ i y ŋ ě]       |
| DORSAL              | [k kʰ x ŋ w ŋ u ũ o õ]              |
| HIGH                | [ʂ ʈʂ ʈʂʰ i y u ũ (k kʰ w)]         |
| LOW                 | [a ã ã̃]                            |
| ATR                 | [(i j) u ũ o õ e]                    |
| RTR                 | [ɕ tɕ tɕʰ ʂ ʈʂ ʈʂʰ]                 |
| NASAL               | [m ɱ ɯ ɨ ə a ã]                      |
| LATERAL             | 1                                     |
| STRIDENT            | [s sʰ ts tsʰ tɕ tɕʰ]                 |
| RHOTIC              | [u ũ o õ e ẽ a ã]                  |

3. Experiments

In this study, we followed a modified model structure based on FastSpeech [23]. We replaced the phoneme input in the original model with a combined set of text input; and then used the FastSpeech acoustic model to generate mel-spectrogram from text. The input text contained SAMPA phonemes [16], prosody features such as punctuations, and lexical tone features. The SAMPA phonemes were then converted into corresponding binary feature using the mapping in [18]. The prosody and tone features were also converted to prosody and tone embeddings respectively. The binary feature and the two embeddings were then concatenated as a text embedding, and was used as the input for the FastSpeech feed-forward transformer. The temporal alignment for the phonemes were obtained through Kaldi [24] ASR tool.

Our modified FastSpeech model consisted of 4 FFT blocks on both the phoneme side and the mel-spectrogram side. For the text, the SAMPA phoneme vocabulary size was 219 (including punctuations); the size of the prosody feature was 4; and the size of the tone feature was 6. The phonemic binary feature was used as the input to a dense layer, and the output size was set to 192. The output of prosody embedding and tone embedding sizes were set to 32 and 32 respectively. The final linear layer output a 128-dimensional mel-spectrogram. All the other parameters were set following what were reported in [23]. We trained our modified FastSpeech model on a NVIDIA GeForce RTX 2080 GPU. We used a batch size 24 for training, and it took 200k steps for training until convergence. The optimizer and other hyper-parameters were the same as those reported in [23]. The output mel-spectrograms of our FastSpeech model were transformed into audio samples using a pretrained MelGAN vocoder [25].

We evaluated all models with a subjective evaluation method, Mean Opinion Score (MOS), surveying listeners’ opinions of the intelligibility of the test utterances. The English utterances were rated by 16 native or near-native English speakers who have more than 10 hours’ daily English usage; the Mandarin data were rated by 19 native Mandarin speakers; and the code-mixing data were rated by 19 bilingual Mandarin-English speakers. We also evaluated the output from the 100h models, which achieved higher intelligibility, with an objective ASR-based measure using Charisu textless phonetic alignment tool [26], and calculated the phone error rate, PER = (deletions + insertions + substitutions) / (entries). Demos for the two experiments are available here: https://congzhang365.github.io/feature_tts/

3.1. Experiment 1: small dataset

In this experiment, we tested whether using phonological features as input could generate intelligible speech with a small amount of data. We examined both the generation of the input language and an unseen language.

Data: The data used in this study were studio-recorded high-quality data, with a sampling rate of 24k Hz, at 16-bit. A set of Mandarin data and a set of English data were used. The English data were recorded by a male, native American English speaker (EN_MS1) in the style of AI assistant, with a total length of 2.62 hours. The Mandarin data were recorded by a male, native Mandarin speaker (CN_MS1) in the style of news reading, with a total length of 20 hours. To test the performance with small data, we designed three intervals of data input:

- M0: 5: 2.62 hours of English, and 0.5 hours of Mandarin
- M2: 2.62 hours of English, and 2 hours of Mandarin
- M8: 2.62 hours of English, and 8 hours of Mandarin

Results: 34 Mandarin-only, English-only, and Mandarin-English code-mixed test utterances were generated using the two voices (EN_MS1, CN_MS1) and with three models for each voice. The MOS results are presented in Table 3.

English utterances: Since the input data contain 2.62h of native English speech, EN_MS1 can produce the English test utterances well from M0.5 onwards. As Table 3 shows, the MOS are higher than 4.5 for all three models. However,
CON MS1, cannot produce intelligible English utterances in any model—all MOS scores are below 1.7. However, the output does present an English-like speech rhythm.

Mandarin utterances: In M0.5, CN MS1 can only vaguely produce the Mandarin utterances (MOS=2.3). Some words were intelligible, but not all. Both M0.5 and M2 have issues with voice quality, lexical tone accuracy, and intonation. In M0.5, CN MS1 can reliably produce intelligible utterances (MOS=4.5), despite some small voice quality issues. EN MS1 cannot produce intelligible Mandarin utterances in any of the three models; all MOS scores are below 2.0. However, if a listener knew the text of the utterance beforehand, the words could be identified very well.

Mandarin-English code-mixed utterances: In M0.5, both EN MS1 and CN MS1 produced identifiable words, with the English speaker being able to produce clearer utterances. M2 presented improvement over M0.5. In M8, both voices produced much clearer utterances in code-switching mode. EN MS1’s output was near ideal; however, it has a lower MOS than the CN MS1’s output due to a lack of lexical tone specification on the Mandarin words.

Table 3: MOS for three models (M0.5, M2, M8) in two voices (Bold: MOS>3.5)

| voice       | CN MS1         | EN MS1         |
|-------------|----------------|----------------|
| model       | M0.5 | M2 | M8 | M0.5 | M2 | M8 |
| English     | 1.31±0.17 | 1.55±0.19 | 1.66±0.18 | 4.54±0.42 | 4.75±0.26 | 4.65±0.39 |
| Mandarin    | 2.34±0.56 | 3.36±0.59 | 4.46±0.48 | 1.62±0.18 | 1.83±0.16 | 1.91±0.14 |
| Code-switch | 2.07±0.58 | 2.97±0.75 | 3.92±0.90 | 2.26±0.19 | 3.09±0.58 | 3.23±0.68 |

3.2. Experiment 2: larger multi-speaker dataset

In this experiment, we used a larger dataset with more speakers and data in both English and Mandarin, in order to test whether using phonological features as input can generate more intelligible output in Mandarin, English, as well as code-mixed utterances with both languages.

Data: A 100-hour multi-speaker dataset was used in this experiment. The dataset contained speech from 12 speakers, including nine native Mandarin speakers and three native General American English speakers. The native English speakers’ data totalled 9 hours. The Mandarin speakers’ data included 5 hours of second-language English speech, 10 hours of code-mixing speech between Mandarin and English, and 76 hours of native Mandarin speech. The test utterances and evaluation procedures in Experiment 1 were also used in this experiment. The following speakers and their data were chosen to generate the test sentences.

- CN FS1: Mandarin-English cross-lingual data by a female native Mandarin speaker. The data consisted of 15 hours of speech in total, including 10 hours of Mandarin speech, 2 hours of English speech, and 3 hours of Mandarin-English code-switching speech. The style and speech materials were designed to build an AI-assistant.
- CN MS2: 9 hours of native Mandarin data by a male native Mandarin speaker. The speech material and style were designed to make announcements and advertise.
- EN MS1: 2.62 hours of English data by a male native American English speaker. The style and speech materials were designed to build an AI-assistant.
- EN MS2: 3.0 hours of English data by a female native American English speaker. The style and speech materials were designed to build an AI-assistant.

Results: The results are shown with both MOS and PER in Table 4 all three voices. Trained with a larger corpus with multi-lingual and multi-speaker data, the outputs from this experiment are much more ideal. All utterances are intelligible and the styles and sentence prosodies are successfully acquired. The results of MOS and PER follow the same pattern: the higher the MOS, the lower the PER. CN FS1 can produce all three language options very well, since the training data include all three language varieties too. CN MS2 could produce Mandarin very well (MOS=4.97), which proves the success of using FUL features in TTS model when the train and test languages are of the same variety. Even though this model does not contain any English data or code-switching data, CN MS2 still produce intelligible English utterances (MOS=3.45). EN MS1’s Mandarin output continue missing the majority of the lexical tones since there is no Mandarin training data in the model; however, it became much more fluent and identifiable than in the previous experiment. The lack of lexical tones makes the English voice sound like a second language learner, and the English outputs from both Mandarin voices also carried heavy Chinese accents.

Table 4: MOS and PER for the 100h-models in three voices (Bold: MOS>3.5; PER<0.25)

|             | CN FS1          | CN MS2          | EN MS1          |
|-------------|-----------------|-----------------|-----------------|
|             | MOS | PER   | MOS | PER   | MOS | PER   |
| English     | 4.45±0.21 | 3.45±0.37 | 4.74±0.18 | 3.45±0.09 | 4.97±0.22 | 3.78±0.47 |
| Mandarin    | 4.98±0.22 | 4.97±0.22 | 3.83±0.31 | 4.93±0.15 | 4.95±0.20 | 3.86±0.15 |
| Code-switch | 4.96±0.24 | 4.95±0.20 | 3.58±0.15 | 4.95±0.10 | 4.95±0.09 | 3.58±0.14 |

4. Discussion and Conclusions

The results showed that using FUL features as input in TTS was indeed feasible, both for a language that is present in the training data and for a language that is not present in the training data. However, we do acknowledge that the results are not yet ideal. One potential reason for the suboptimal performance is at the forced alignment stage. The forced alignment tool was trained on an ARPABET or pinyin, while our text input was based on a more fine-grained phoneme set, SAMPA. Errors therefore might have occurred in the forced alignment process, leading to bad cases that made the output less intelligible. We thus are also developing more accurate ways of automatically aligning the audios to phones.

Apart from the possibility of applying FUL features in TTS application to synthesise multi-lingual data, the findings of this study have also provided strong supporting evidence for the validity of the FUL model. In FUL theory, listeners first extract the features from the auditory input data. The extracted features are then mapped onto the underlying contrasts of the listeners’ native language. The listeners or speakers then add the phonological rules and processes of their native language to produce non-native speech [15]. The accentuatedness in second language production can be explained by this theory. Our findings of English speaker lacking tonal contrasts and Mandarin speaker having Mandarin-like vowels in English utterances both support this process. Typologically, the investigation of tonal and non-tonal languages in this study contributed to the general investigation of applying phonological features in TTS (c.f. [1], [27]) for languages with different ways of prosodic specification on a lexical level.
5. References

[1] M. Staib et al., “Phonological features for 0-shot multilingual speech synthesis,” Proc. Ann. Conf. Int. Speech Commun. Assoc. INTERSPEECH, vol. 2020-Oct, pp. 2942–2946, 2020, doi: 10.21437/Interspeech.2020-1821.

[2] A. Guflin, M. Jansche, and T. Merkulova, “Fonbund: A library for combining cross-lingual phonological segment data,” 2018 - 11th Int. Conf. Lang. Resour. Eval., pp. 2236–2240, 2019.

[3] G. Maniati et al., “Cross-lingual low resource speaker adaptation using phonological features,” in Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH, 2021, vol. 5, pp. 3386–3390, doi: 10.21437/Interspeech.2021-327.

[4] D. Wells and K. Richmond, “Cross-lingual Transfer of Phonological Features for Low-resource Speech Synthesis,” in 11th ISCA Speech Synthesis Workshop, 2021, pp. 160–165, doi: 10.21437/ssw.2021-28.

[5] S. Moran, “Using Linked Data to create a typological knowledge base,” in Linked Data in Linguistics, Springer, 2012, pp. 129–138.

[6] D. R. Mortensen, P. Littell, A. Bhandwaj, K. Goyal, C. Dyer, and L. Levin, “Panphon: A resource for mapping IPA segments to articulatory feature vectors,” in Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers, 2016, pp. 3475–3484.

[7] D. Dadiu and S. Moisk, “Defining and counting phonological classes in cross-linguistic segment databases,” in LREC 2016: 10th International Conference on Language Resources and Evaluation, 2016, pp. 1955–1962.

[8] N. Chomsky and M. Halle, “The sound pattern of English,” 1968.

[9] A. Lahiri and H. Reetz, “Underspecified recognition,” Lab. Phonol., 2002.

[10] A. Lahiri, “Predicting universal phonological contrasts,” L. M. Hyman and F. Plank, Eds. De Gruyter Mouton, 2018, pp. 229–272.

[11] V. Arora, A. Lahiri, and H. Reetz, “Phonological feature-based speech recognition system for pronunciation training in non-native language learning,” J. Acoust. Soc. Am., vol. 143, no. 1, pp. 98–108, 2018, doi: 10.1121/1.5017834.

[12] S. Kotzor, A. Wetterlin, and A. Lahiri, “Symmetry or asymmetry: Evidence for underspecification in the mental lexicon,” in The Speech Processing Lexicon, A. Lahiri and S. Kotzor, Eds. De Gruyter Mouton, 2017, pp. 85–106.

[13] N. Albaster-Mackensen and P. Fikkert, “The acquisition of the stop-fricative contrast in perception and production,” Lingua, vol. 120, no. 8, pp. 1989–1990, 2010, doi: https://doi.org/10.1016/j.lingua.2010.02.010.

[14] I. Roste, S. L. Frank, and P. Fikkert, “Modeling the Influence of Language Input Statistics on Children’s Speech Production,” vol. 44, 2020, doi: 10.1111/cogs.12924.

[15] M. Ghini, “Place of articulation first,” in Distinctive feature theory, T. A. Hall, Ed. De Gruyter Mouton, 2012, pp. 147–176.

[16] J. C. Wells, “SAMPA computer readable phonetic alphabet,” Handb. Stand. Resour. Spok. Lang. Syst., vol. 4, pp. 684–732, 1997.

[17] J. Zhang, “Hanyu Putonghua Jidu Yinbiao SAMPA-SC [SAMPA-SC for standard Chinese (Putonghua)],” Shengyue Xuexiao, 2009.

[18] C. Zhang and H. Zeng, “Phonological feature mapping for FeatureTTS.” Oct. 07, 2021, doi: 10.5281/ZENODO.5535685.

[19] R. Jakobson, G. Fant, and M. Halle, “Preliminaries to speech analysis: The distinctive features and their correlates,” Tech. Rep. No. 13, 1952.

[20] A. Lahiri and H. Reetz, “Distinctive features: Phonological underspecification in representation and processing,” J. Phon., vol. 38, no. 1, pp. 44–59, Jan. 2010, doi: 10.1016/j.wocn.2010.01.002.

[21] S. Duanmu, The Phonology of Standard Chinese, 2nd ed. Oxford University Press, 2000.

[22] S. I. Lee-Kim, “Revisiting Mandarin ‘apical vowels’: An articulatory and acoustic study,” J. Int. Phon. Assoc., vol. 44, no. 3, pp. 261–282, 2014, doi: 10.1017/S0025100114000267.

[23] Y. Ren et al., “FastSpeech: Fast, robust and controllable text to speech,” Adv. Neural Inf. Process. Syst., vol. 32, no. NeurIPS, 2019.

[24] D. Povey et al., “The Kaldi speech recognition toolkit,” in IEEE 2011 workshop on automatic speech recognition and understanding, 2011, no. CONF.

[25] K. Kumar et al., “Melgan: Generative adversarial networks for conditional waveform synthesis,” arXiv Prepr. arXiv1910.06711, 2019.

[26] J. Zhu, C. Zhang, and D. Jurgens, “Phone-to-audio alignment without text: A Semi-supervised Approach,” IEEE Int. Conf. Acoust. Speech Signal Process., 2021, [Online]. Available: http://arxiv.org/abs/2110.03876.

[27] A. Guflin, L. Ha, M. Jansche, K. Pipatsrisawat, and R. Sproat, “TTS for low resource languages: A Bangla synthesizer,” Proc. 10th Int. Conf. Lang. Resour. Eval. Lr. 2016, pp. 2005–2010, 2016.