Pronunciation Generation for Foreign Language Words in Intra-Sentential Code-Switching Speech Recognition

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1. Introduction

Code-Switching (CS) is a common oral phenomenon for many multilingual speakers that different languages coexist in sentences. As (Sankoff and Poplack, 1981) defined, CS can be categorized into inter-sentential switching and intra-sentential switching. In the intra-sentential case we focus on in this paper, foreign words usually appeared in a native language sentence as loan words. Compared with monolingual automatic speech recognition (ASR) systems, the hindrances in the CS recognition are summarized as follows: (1) the lack of CS training data, (2) the phonemes difference in different languages, (3) the accent issues on foreign languages spoken by native language speakers.

In recent years, the related works in tackling CS have been continuously deepened. Some mainstream methods focus on building the mixed-language acoustic model (AM) and the language model (LM). Due to the limited CS speech data, the phoneme-sharing method in multiple languages has been applied broadly to decrease the size of mixed-language AM units, where the sharing methods can be divided into phoneme-merging (Lin et al., 2009; Li et al., 2011; Sivasankaran et al., 2019) and using a universal phoneme set such as IPA (Smith, 2000) generally, however, those may increase the risk of inter-language substitution errors due to renaming the context of some triphones in each language. Some multi-task-learning (MTL) technologies (Huang et al., 2013; Yilmaz et al., 2016) also have been explored in CS, where the recognition for accented speech (Mendes et al., 2019) and the recognition around the switching position (Chen et al., 2016b) have been improved by transferring knowledge between different tasks. Generally, in the intra-sentential CS case, the main part of speech is still native language (NL) and foreign words occupy less often, therefore, under the commissioned native language acoustic mode (NL-AM) that shows good recognition and robustness in the real scenario since it has abundant training data, it is a valuable work to explore a shortcut to preserve its stability in native language and extend its capability to foreign words.

For intra-sentential CS speech recognition, this paper proposes a data-driven scheme to generate mapping pronunciations for foreign words to meet intra-sentential CS speech recognition, concretely, the reliable pronunciations are given by the Grapheme-to-Phoneme (G2P) model which was trained on the seed lexicon, where making this seed lexicon is a core data-driven work and this paper adopts phonetic decoding for candidate generation and average posterior estimation (APE) or phoneme Confusion Network (PCN) for candidate selection. Compared with the seed lexicon made by (Huang et al., 2019), this paper proposes the following improvements: (1) A purely data-driven approach without any linguist pronunciation labeling. (2) In acoustic-based candidate selection, we adopt the average utterance-level posterior probability of candidate to give an acoustic score. (3) For pronunciation prediction, we use the popular transformer-based (Zhang et al., 2017) sequence-to-sequence (seq2seq) architecture in natural language processing (NLP) field to design our G2P model.

However, foreign words’ different occurrences in the CS corpus lead to imbalanced word-level driving materials in the data-driven approach, which further cause imbalanced driving processing, and the pronunciation qualities...
with fewer materials always show poor performance. In this work, for the imbalanced driving material issue, we further propose an internal assistance strategy between the words with sufficient materials and the words with scarce materials to improve the pronunciation qualities in the seed lexicon overall.

The rest of this paper is organized as follows. Section 2 is a summary of related works on retraining-free and phonetic decoding methods for CS. Section 3 describes candidate generation and selection methods for seed word pronunciation. Section 4 introduces the pronunciation prediction works that contain building seed lexicon, describing the architecture of the transformer G2P model and proposing a novel internal assistance method to improve the seed lexicon. Section 5 gives the detailed experimental configuration and result. Section 6 concludes the advantages of the proposed methods and lists some valuable future works.

2. Related Works

Compared to the available data in monolingual ASR, the CS corpus is very limited (Ganjii et al., 2019; Lyu et al., 2010; Li et al., 2012; Shen et al., 2011; Chan et al., 2005; Lyu et al., 2006), hence some CS recognizers adopt the retraining-free methods that expand new language recognition capabilities in existing monolingual ASR system instead of rebuilding mixed-language AM/LM. (Yu et al., 2009) proposed and compared four approaches for CS recognition under the constraint of native language acoustic model (NL-AM) in real-time, in that case, the foreign words were expressed in the native language phonemes set through phoneme/senone mapping using the least Kullback-Leibler Divergence, and achieved the best result among the AM merging techniques. Base on the NL-AM, Pronunciations Generation in foreign words is considered as another low-cost solution for intra-linguistic transcription. (Bhuvanagiri and Kopparapu, 2010) and (Bhuvanagiri and Kopparapu, 2012) built a Hindi-English ASR system based on the existing monolingual AM using the mapped lexicon and the modified language model. (Modipa et al., 2013) constructed the Sepedi-English ASR system based on a Sepedi speech decoder, where the pronunciations of English words were obtained from the Sepedi language phonetic decoder and then added into the original lexicon. (Huang et al., 2019) obtained high-quality foreign words’ pronunciations from a grapheme-to-phoneme (G2P) model trained on linguist/data-driven lexicon, where the data-driven method consisted of a phonetic decoding on foreign words spoken by native language speakers generating method and a rover-like (Fiscus, 1997) Phoneme-Confusion-Networks with acoustic score ranking method. Also, in building mixed-language AM for the Mandarin-English CS task, (Guo et al., 2018) adopted phonetic decoding method to correct mismatched pronunciations by decoding.

3. Pronunciation Generation For Seed Word

This section mainly introduces the data-driven way to obtain good pronunciations of foreign seed words. Approaches in generating pronunciations can be divided into manual and data-driven categories. On the manual side, people will consider the rationality on pronouncing perception, but that may be time-consuming and imprecise due to accent problems which are often neglected. On the data-driven side, we will use phonetic decoding technology where the decoding results are consistent with the similarity in acoustics and take native accents into account.

The phonetic decoding method is a data-driven way to obtain foreign words’ pronunciations, that is, the NL-AM based phonetic decoder is used to decode the foreign words’ audio segments to obtain the native phoneme sequence as candidate pronunciations. The source to obtain foreign words’ audio segment is mainly derived from the speech data of native or foreign speakers, due to the CS speech recognition task is oriented to native speakers, in this article we use the audio segments in a limited CS corpus spoken by native speakers as driving materials.

3.1. Extracting Audio Segments

For foreign words’ audio segmentation, we need to first obtain their start/end timestamps. The timestamp acquisition is achieved by speech-text forced alignment on the AM, and the general method is to build mixed-language GMM-HMM based AM with a combination of native language lexicon and foreign language lexicon. (Huang et al., 2019) maintain the retraining-free way that they used foreigner’s audio segments as driving materials to obtain mapped lexicon by phonetic decoding to execute forced-alignment on the NL-AM, though this method avoided pre-training a mixed-language AM, but foreign words’ pronunciations with foreign accent may cause inaccurate alignments. In this work, we still choose to pre-train a mixed-language GMM-HMM based AM for alignment and segmentation of foreign words.

3.2. Phonetic Decoding

Different from the word-level ASR system, a phonetic decoder is built on the decoding graph with a phoneme-level LM. Based on the NL-AM, we build a phonetic decoder \( P \), and then decode the foreign words’ audio segments in high acoustic weight setting to obtain the native language phoneme sequences with high acoustic similarity.

For a foreign language word \( w \), we extract its embedded utterances subset \( O_w = \{ O_1, O_2, \ldots, O_{M_w} \} \) in the limited CS corpus, where \( M_w \) denotes the number of utterances which contain the word \( w \). As subsection 3.1 introduces, we extract its segments set \( S_w \) in \( O_w \) through forced-alignment in mixed-language GMM-HMM:

\[
S_w = \{ s_i \mid i = 1, 2, \ldots, k \}
\]  (1)
where $S_w$ collects $k$ segments from $O_w$ ($k \geq M_w$ because there is at least one per utterance), also the $k$ means the driving volume of $w$ in the data-driven approach. Then each segment $s$ in $S_w$ will be fed into phonetic decoder $P$ and get the $n$ best results:

$$P(s) = \{p_1, p_2, \cdots, p_n\} \quad (2)$$

Finally, we will merge all decoding results into an initial candidates set $\Phi_w$ for $w$:

$$\Phi_w = P(s_1) \cup P(s_2) \cup \cdots \cup P(s_k) \quad (3)$$

### 3.3. Candidate Selection

From subsection 3.2, we utilize phonetic decoding approach as the source for producing candidate pronunciations to foreign words, but those decoded candidates may include a lot of noises due to the acoustic difference in different languages and the possible inaccurate segments-cutting. Hence, we need to filter and select from these raw candidates to obtain high-quality candidates which can bring good recognition results, here we will introduce some selection methods in this section.

#### 3.3.1. Average Posterior Estimation

In data-likelihood-reduction based pronunciation selection criterion, (Zhang et al., 2017) collected the acoustic evidence using conditional data likelihood of utterance $O_u$ given the pronunciation of word $w$ being candidate $b$: $\tau_{u,w}^{p,b} = P(O_u | w, b)$, then they replaced $\tau_{u,w}^{p}$ with the posterior statistic $Y_{u,w}^{p} = P(w, b | O_u)$ by Bayes’ rule and further removed low-quality candidates by comparing their average utterance-level posterior statistics. Similarly, we evaluate the overall acceptance in original utterances by calculating the average utterance-level posterior probability to each candidate with the following formula:

$$Y_{u,w}^{p} = \frac{1}{M_w} \sum_{w=1}^{M_w} P(w, p | O_u) \quad (4)$$

where $P(w, p | O_u)$ represents the posterior probability of $w$ pronouncing $p$ in the utterance $O_u$. According to the comparison of $Y_{u,w}^{p}$, we can get the ranked table in initial candidates $\Phi_w$ and select the best results subsequently. A pronunciation selecting example to the foreign word *office* in Chinese-English CS is showed in Figure 1.

#### 3.3.2. Phonoeme Confusion Network

Another novel approach in selecting candidates is to combine the best results on initial candidates. (Huang et al., 2019) proposed to build a phoneme confusion network (PCN) on the candidates of a particular word to combine the most generalized candidates (voting-based), where building PCN is a ROVER-like (Pisticci, 1997) method that all candidate sequences are combined into a single, minimal cost word transition network via iterative applications of dynamic programming alignments. For example, we get 10 candidates of the word *health* from phonetic decoder:

1. h ai2 ii iu5 x i3
2. h ai2 ii iu5
3. h ai2 ii iao1 x i2
4. h ai2 ii iao4
5. h ai2 ii iao1 x i4
6. h ai2 ii iao1 x i1
7. h ai2 ii iao1 x i3
8. h ai2 ii iao2 s iy3
9. h ai2 ii iao3 s iy3
10. h ai2 ii iao4 s iy3

then the corresponding phoneme confusion network is built as Figure 2 shows, where the numbers in parentheses represent the number of times a phoneme appears and we can summary 4 best phoneme sequences (with most votes) for ‘*health*’:

1. h ai2 ii iao1 x iy3
2. h ai2 ii iao1 x i3
3. h ai2 ii iao1 s iy3
4. h ai2 ii iao1 x i1

It is worth noting that the summary results from PCN may produce new variants such as the result ‘h ai2 ii iao1 x iy3’ which has not appeared in original candidates.

### 4. Pronunciation Prediction

For various CS scenarios, we want to achieve the pronunciations of any foreign word (including out-of-set foreign words), but our available pronunciations come from the closed set $F$ composed of all foreign words in the CS corpus. Grapheme-to-Phoneme (Rugchatjaroen et al., 2019; Bisani and Ney, 2008; Bellegarda, 2005) approach is the process of converting the written form to the pronunciation of a word and is a seq2seq method from character sequence to phoneme sequence essentially. In this paper we use a G2P model to learn the pronunciation rules in the best candidates of closed set $F$, that is, we collect all best candidates of $F$ using the data-driven method to build the seed lexicon, then our G2P model will be trained on this lexicon and predict possible pronunciations for any foreign word.

#### 4.1. Building the Seed Lexicon

The seed lexicon plays an important role in training G2P model. In traditional work, the to the G2P model is an expert-knowledge based seed lexicon, but the seed lexicon in our method consists of all foreign words’ best decoding results through the data-driven method, and the trained G2P model will possess the mapping rules in pronouncing. This paper extracts all foreign words’ audio segments in the CS corpus as driving materials, and then obtain all foreign words’ n-best candidates through phonetic decoding and selecting methods, finally all candidates are gathered into a seed lexicon used as to G2P model.
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Figure 1: Average posterior estimation on the candidates of the foreign word office in Chinese-English CS.

Figure 2: Phoneme confusion network built with 10 candidates for word ‘health’

4.2. Transformer-based G2P Model

Many approaches in sequence modeling and transduction problems generally adopt recurrent neural networks (Kleeman and A, 2020; Karev and Suykens, 2020; Jiang et al., 2020; Gao et al., 2020), but transformer (Vaswani et al., 2017) model architecture discards the recurrence module and instead relies entirely on the attention mechanism to draw global dependencies between input and output, which has successfully achieved better results in natural language processing (NLP) tasks (Huang et al., 2020; Chen and Li, 2020; Ángel González et al., 2020) such as Neural Machine Translation. In the encoder-decoder architecture of the transformer, the multi-head attention mechanism is widely used so that the model can learn relevant information in different representation sub-spaces. Multi-head attention projects vectors Q(query), K(key), V(value) through h different linear transformations, and then the different attention results are concatenated together:

\[ \text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O \]

where each head is represented:

\[ \text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \]

the attention approach adopts the scaled dot-product:

\[ \text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right)V \]

In the above formulas, softmax is a activation function used to calculate attention weight, W represents the weight matrix and \( d_k \) represents the output feature vector dimension. In our work, we use the transformer based G2P model to translate the foreign word from written-form to pronunciation representation in the native language phoneme set, which model is different from the seq2seq-based G2P model proposed in (Huang et al., 2019; Rao et al., 2015).

4.3. Improving the Seed Lexicon

In the data-driven processing, the amount of the data used for driving often determines the quality of the results, and more driving materials often have more generalized and diverse results. In this paper, the amount of foreign words’ audio segments will determine whether to generate a more generalized and high-quality pronunciation and solve problems such as the accent diversity in different native speakers. However, in the limited CS corpus, different appearance frequencies cause unequal available materials to different foreign words, which further lead to imbalanced driving processing and different qualities of candidates.

4.3.1. Motivation

In order to better explain the problem about imbalanced driving materials, we propose a metric ARR (average recall rate), which describes the relationship between recognition accuracy and driving volume (i.e. the number of audio segments) for foreign pronunciation (see Equation 5)

\[ \text{ARR}_B = \frac{1}{N_B} \sum_{w \in B} \frac{P_w}{T_w}, \quad k_w \in B \]
In Equation 5, \( B \) represents a limited driving volume interval, \( k_w \) represents the driving volume of word \( w \), \( N_B \) denotes the number of foreign words in interval \( B \), \( P_w \) and \( T_w \) represent the successful recognition count and the true occurrence count of word \( w \) respectively, and higher ARR means that better pronunciation quality in CS speech recognition. For example, Figure 3 shows the ARR results with the pronunciations of 880 English words by phonetic decoding and APE method in the 5780 utterances of our Chinese-English intra-sentential CS experiment, and we could observe that the pronunciations generated under small driving volume had poor performance. Such a result may be attributed to the bottleneck in generating candidates, and unreliable score on a small number of utterances.

**Figure 3:** Average recall rate of English words with different driving volume intervals in 5780 Chinese-English code-switching utterances.

### 4.3.2. Internal Assistance

Due to insufficient driving data leading to poor recognition, we hope the pronouncing rules learned with adequate driving materials will provide extra helpful candidates to the scarce data. First, in the raw CS corpus, we define the minimum driving volume limit \( K \) to screen the audio segments of the foreign words whose driving volume is not less than \( K \) as a driving material set \( DM_K \), which ensures a more reliable seed lexicon can be obtained. In the limited CS corpus, a larger \( K \) means more reliable driving results in the seed lexicon, but it brings a smaller seed lexicon which is not beneficial to training G2P model, so we should weigh the setting of \( K \).

In this work, for the APE based data-driven process, we propose an internal assistance (IA) strategy to improve the pronunciation in scarce materials (see Figure 4). As Figure 5 shows, in the material set \( DM_K \) with the restriction \( K \), we divide \( DM_K \) into the sufficient set \( DM_K^A \) and the scarce set \( DM_K^B \) by a threshold line (volume) \( P \) we pre-defined \( (P > K) \), and then use the data-driven results lexicon0 of \( DM_K^A \) to train a G2P model to learn high-quality pronunciation rules, and give foreign words in \( DM_K^B \) extra reference pronunciations lexicon1. Next, we use the APE method to select best candidates between the data-driven results lexicon2 of \( DM_K^B \) and lexicon1 to obtain the improved lexicon3 for \( DM_K^B \). Finally, lexicon0 and lexicon3 were merged and used as a seed lexicon to train our final G2P model.

**Figure 4:** The proposed internal assistance inspiration is shown on the heat-map of pronunciation quality, where the scarce section will be improved.

**Figure 5:** The G2P model trained on the sufficient set \( DM_K^A \) is giving the words in the scarce material set \( DM_K^B \) extra reference pronunciations

### 5. Experiment

Our CS experiments were aimed at Chinese and English intra-sentential CS speech recognition, where Chinese and English were native language and foreign language respectively. Assuming that the language model supported Chinese-English mixed grammar, we developed the recognition ability for English words on the existing Chinese AM, and had compared different seed lexicons generated by different methods.

#### 5.1. Data

Our experiments were carried out on the data for ASRU2019 Mandarin-English Code-Switching Challenge provided by Datatang AI Dataset \(^2\), as Table 1 showed, the speech data spoken by Chinese people using telephone consisted of 500 hours Mandarin training speech data (\( data_A \)), 200 hours inter/intra-sentential Mandarin-English CS training speech data (\( data_B \)) and 20 hours inter/intra-sentential Mandarin-English CS testing speech data (\( data_C \)), additionally the 3gram Chinese-English mixed-language LM was offered also. We used \( data_A \) to train NL-AM, \( data_B \) to obtain driving materials for foreign words, in order to reduce the impact of the spelling pronunciation of abbreviations, we only considered English words with a length of more than 3 letters and cleaned the \( data_C \) to obtain a subset \( data_C^* \) \(^3\), and \( data_C^* \) was used as the final test set. Moreover, we built Chinese ASR system using the existing NL-AM and the offered mixed-language LM.

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\(^2\)www.datatang.ai

\(^3\)Many acronyms in the \( data_C \) were generally short in length, such as UFO, NBA, etc.
5.2. Preparation Works

This part introduced some preparations about the setting of phoneme sets, the construction and testing of NL-AM, and the preparation of phonetic decoder and mixed-language GMM-HMM in the data-driven.

**Phoneme-set:** As the phoneme-setting, we chose phonemes from the Chinese lexicon (Bu et al., 2018) and the English lexicon for AM units, and we shrunk the size of English phonemes-set by merging variants to alleviate the intensity on sparse English-part in CS utterances, which resulted into 214 Chinese phonemes and 39 English phonemes to NL-AM or mixed-language GMM-HMM.

**NL-AM:** In preparing NL-AM, we split data A into 95% part to train Chinese NL-AM and 5% part to validate Chinese NL-AM, the model was composed of 40-dimensional MFCC (Mel Frequency Cepstral Coefficients) and 3-dimensional pitch input features, 6 layers (625 nodes per layer) Time Delay Neural Network (Peddinti et al., 2015) with LF-MMI (Povey et al., 2016) training method and 3944 clustering nodes. As a result, we got an 8.81% character error rate (CER) on the 5% part.

**Phonetic decoder:** Our phonetic decoder was built on the NL-AM and the bi-gram phonetic LM trained on the alignment results of data A, then we got accented phoneme sequences with high acoustic weight from this decoder.

**Audio segmentation:** The timestamps for segmentation were obtained through forced-alignment on the Chinese-English mixed-language GMM-HMM model trained on data B, where the model units were a union of Chinese phonemes and English phonemes.

**LM weight:** We adopted the LM weight using parameter tuning, optimizing the integer value in the interval of 7 to 17 on the validation set.

5.3. Seed lexicon and G2P model

This part mainly introduces the core works in building the seed lexicon and the configuration of transformer-based G2P model.

**Driving material:** In building the seed lexicon work, we wanted to collect as high quality and sufficient candidates as possible. As mentioned in subsubsection 4.3.2, we considered 10/20/30 \( k \) settings to make the driving material set. The size of foreign words and total driving volume of material sets with different \( k \) were showed in Table 2.

**Phonetic decoding:** First we performed the forced alignment operation on the mixed-language GMM-HMM to obtain the timestamps of foreign words, then cut out segments and sent these segments to the NL-AM based phonetic decoder. In the decoding process, we set a high acoustic weight in order to pursue the real accent.

**APE method:** We referred to the interface provided by (Zhang et al., 2017) in kaldi-tools (Povey et al., 2011) to calculate the posterior probability in the original sentence for each pronunciation. In the calculation process, sentences generated their lattices which saved the alignment information of multiple candidate pronunciations, and then we counted the average posterior probability in all host sentences for a specified pronunciation. Same as (Zhang et al., 2017), we filtered out low-quality pronunciation through the first APE method and then re-generate lattices to re-calculate the posterior probability, and this pruning helped to improve the accuracy of the posterior probability.

**PCN method:** In the construction of the PCN, we used the rover method in SCTK-tool (Fiscus, 1997) to align multiple candidates, and then counted the voting information on each edge to calculate the best paths with the highest scores as the best candidates.

**G2P model:** Our transformer-based g2p model used 3-layer encoders/decoders and 4-head attentions by building on the tensor2tensor library (Vaswani et al., 2018).

5.4. Metric

We adopt the mixed error rate (MER) to evaluate the recognition accuracy in CS scenario, where the accuracy of Chinese recognition was calculated by characters, and the accuracy of English recognition was calculated by words. In addition, we used the recall rate to approximate the Chinese character error rate (CER) and the English word error rate (WER). For example, as Figure 6 showed, there were four types of alignment: C:correct, S:substituting, I:Inserting and D:deleting, we could calculate: MER:2/8=25.0%, CER (Chinese):1-6/7=14.3%, WER (English):1-0/1=100.0%.

5.5. Experimental Variables

We considered and obtained different seed lexicons with the following setting:
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Table 3
The Chinese-English CS test-set results with only Chinese lexicon loaded

| CH(%) | EN(%) | MIX(%) |
|-------|-------|--------|
| 21.5  | 100.0 | 29.15  |

- **material set** $DM_{K}$: specifying the minimum driving volume limit $K$.
- **selecting method**: APE or PCN method.
- **internal assistance (IA)**: whether to use IA method in seed lexicon with threshold line $P$.

All seed lexicons in our experiment trained their G2P models under the same training configurations, then these G2P models gave 4 candidate pronunciations for each English word in the test set. The pronunciation model we adopted the all-one pronunciation probability for all words.

5.6. Results

We have completed the following experiments on the 17 hours ASRU2019 Chinese-English CS test-set (data $C^*$. First, as Table 3 showed, we sent our CS test-set into Chinese ASR system with Chinese lexicon loaded only and got results: 21.5% CER in Chinese part, 100.0% WER in English part, and 29.15% MER overall. Surely the Chinese ASR system couldn’t support English words recognition and high WER (for English) caused high CER (for Chinese) because of more insertion errors occurring in the Chinese parts.

Next, as Table 4 showed, we made the leap from zero to one on foreign words’ recognition, we added predicted pronunciations of all English words in test-set from G2P models trained on different seed lexicons into the lexicon of Chinese ASR system. In the data-driven process, though the larger the restriction $K$, the more reliable pronunciations in seed lexicon could be, but the smaller seed lexicon was not good to train the G2P model, the results showed that the larger driving material set achieved better results, where we trained the better G2P model on the seed lexicon obtained by phonetic decoding and APE method in materials $DM_{10}$, the pronunciation of English words in the test-set predicted by this G2P achieved 38.75% WER in English and 12.13% MER overall, this result we deemed as a baseline.

For the imbalanced driving material issue mentioned in subsubsection 4.3.1, we defined two threshold lines $P = 20$ and $P = 30$ in $DM_{10}$, and we compared the assistance of $DM^A_{10}(P = 20)$ to $DM^B_{10}(P = 20)$ and the assistance of $DM^A_{10}(P = 30)$ to $DM^B_{10}(P = 30)$. The results showed that this internal assistance (IA) method had substantial improvement on the quality of the seed lexicon compared to the baseline. The smaller $P$ has achieved better results and the MER has dropped from 12.13% to 11.87% with $P = 20$.

We then tried to use PCN instead of the APE method to select good candidates. Since there were too many initial phonetic decoding results for each foreign word and that were to greatly increase the computation in batch decoding on PCN, so we had used the APE method to screen a small number of high-quality candidates. In our experiment, $PCN_1$ represented a confusion network built on $n$ candidates, and then we used the majority voting strategy on the confusion network to obtain the best summary results. We compared the summary results from the confusion network constructed on 5/10/20 candidates, and experiments showed that the confusion network constructed on more candidates was to generate better summary results, where $PCN_{20}$ got 13.45% MER. However, new variants appeared but original candidates disappeared in the summary results might not perform better, on the whole, it was still slightly worse than the APE method when we directly used the PCN method to build the seed lexicon.

Since some new variants in PCN summary results might be good candidates, we kept the original candidates and performed the posterior estimation again between the new variants and the original candidates. The results showed that the PCN/APE hybrid method could further improve the quality of the seed lexicon based on the baseline, and the $PCN_{20}$ and APE hybrid method reached 11.19% MER.

Finally, on the basis of the PCN/APE hybrid method, we further added the internal assistance method and the experimental results showed that the recognition result was further improved slightly and reached the best MER 11.14%. In summary, the seed lexicon obtained by the PCN/APE/IA hybrid method achieved the best recognition in the intra-sentential CS scene.

6. Conclusion

In this paper, we explore a shortcut to develop intra-sentential code-switching speech recognition in existing NL-AM, where the core work is to obtain the real accented pronunciation which is mapped into a native language phoneme sequence. To directly build a mixed-language acoustic model for the CS task with a limited CS corpus may be costly and limited performance, instead, we make use of the limited CS corpus and take it as driving material to generate foreign words’ pronunciation to meet intra-sentential CS speech recognition task under the NL-AM.

We propose a data-driven method to create a seed lexicon for training the G2P model to predict the possible pronunciations of any foreign word, where the pronunciation quality of the seed lexicon determines the reliability of prediction. In our experiment we utilize the phonetic decoding method as the source to produce candidates and compare the different selection methods to screen good candidates. Phonetic decoding as a data-driven approach tends to obtain candidates with high acoustic similarity and does well in generating...
the native accented pronunciations, and the decoding results from the decoder are often rich and diverse, but contain a lot of noise. Hence, for the following screening work, we try the acoustic-based average posterior estimation (APE) (Zhang et al., 2017) method and the summary-based phoneme confusion network (PCN) (Huang et al., 2019) method to give n-best candidates. It is worth noting that the ROVER-like (Fiscus, 1997) PCN method may produce new variants and also at the same time lose the original candidates from the phonetic decoder, so we adopt the PCN/APE hybrid approach to further improve seed lexicon.

However, for different foreign words in the limited CS corpus, the imbalanced driving materials lead to imbalanced driving processing. We therefore developed an internal assistance approach which is to give extra reference candidates to the scarce materials by learning the pronunciation rules in the sufficient materials, where the division of the scarce/sufficient set is determined by the threshold line (i.e. a specified driving volume). Experiments have shown that this internal assistance will further improve the pronunciation quality of the seed lexicon.

Finally, we continue to add internal assistance trick to PCN/APE hybrid method, and experiments show that the PCN/APE/IA hybrid method has a further slight improvement and achieves the best recognition error rate in the intra-sentential CS scenario. In fact, in addition to phonetic decoding, PCN and internal assistance method can provide additional meaningful variants, some of them may perform better in the recognition task.

There are still many unexplored ways to improve the seed lexicon. Under the limited CS corpus, the source to generate candidates for seed lexicon in this article mainly comes from the phonetic decoder, and some new variants generated by PCN or IA method may bring better performance. In future work, we will focus on searching more sources for generating foreign words’ pronunciation to improve the pronunciation quality of seed lexicon.

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