Exploring Retraining-Free Speech Recognition for Intra-sentential Code-Switching

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Abstract

In this paper, we present our initial efforts for building a code-switching (CS) speech recognition system leveraging existing acoustic models (AMs) and language models (LMs), i.e., no training required, and specifically targeting intra-sentential switching. To achieve such an ambitious goal, new mechanisms for foreign pronunciations and language model (LM) enrichment have been devised. Specifically, we have designed an automatic approach to obtain high quality pronunciation of foreign language (FL) words in the native language (NL) phoneme set using existing acoustic phone decoders and an LSTM-based grapheme-to-phoneme (G2P) model. Improved accented pronunciations have thus been obtained by learning foreign pronunciations directly from data. Furthermore, a code-switching LM was deployed by converting the original NL LM into a CS LM using translated word pairs and borrowing statistics for the NL LM. Experimental evidence clearly demonstrates that our approach better deals with accented foreign pronunciations than techniques based on human labeling. Moreover, our best system achieves a 55.5% relative word error rate reduction from 34.4%, obtained with a conventional monolingual ASR system, to 15.3% on an intra-sentential CS task without harming the monolingual recognition accuracy.

Index Terms: multilingual speech recognition, code-switching, grapheme-to-phoneme

1. Introduction

Code-switching (CS) is usually referred to as the situation where a speaker alternates between different languages within a single conversation, e.g., [1] [2] [3] [4]. Code-switching can be broadly divided into two groups [5]: inter-sentential switching - the alternation is between sentences (also called extra-sentential), and intra-sentential switching - the alternation is within sentences (it can also include intra-word). With the rapidly growing of bilingual/multilingual population, CS is no longer a phenomenon relevant for minority languages, which are affected by majority languages, but it also concerns major- ity languages influenced by lingua francas, such as English and French, as properly pointed out in [6]. Despite the recent significant advances witnessed in the field of automatic speech recognition (ASR) [7], ASR systems have unfortunately still limited capability in tackling the code-switching problem, especially intra-sentential switching. Major challenges for CS speech recognition include different phone sets among languages, and insufficient intra-sentential code-switching training data.

In recent years, we have witnessed an increasing research effort to address the CS problem, and available approaches can mainly be divided into two groups: robust acoustic modeling, and language modeling. For example, a global phoneme set is constructed by merging phoneme sets from different languages, and a unified multilingual acoustic model (AM) is trained in [8] [9] [10]. However, the goal of those studies on cross-language AMs is to develop ASR systems for new languages for which scarce or no training material is available. In the CS scenario, the native language (NL) AM should be used at the runtime, and the recognition accuracy and speed for the NL ASR should not be sacrificed. In [11], the authors compared four ASR approaches to tackle the CS task under the constraint that the NL AM is to be used at runtime. In those approaches, the lexicon in the foreign languages (FLs) are represented by the NL phoneme set through phone/senone mapping/merging using either knowledge-based or data-driven mapping techniques, and the NL acoustic model (AM) is employed to carry out recognition. It was shown that top recognition results were obtained by mapping each senone in the FL’s AM to the senone in the NL’s AM with the minimum Kullback-Leibler divergence. From a language model (LM) point of view, a statistical machine translation (SMT) based text generation technique was used in [12] to artificially augment the amount of training data to estimate more robust LMs. In [13], a multi-lingual LM is trained by combining monolingual LMs into a probabilistic finite state grammar. More recently, syntactic and semantic features were integrated into a factored language model to combat data scarcity in code-switching speech [14]. Recurrent neural networks (RNNs) and factored language models are instead combined in [15] for improved CS performance. In [16], the authors successfully used similar word pairs to borrow information from available (already trained) monolingual LMs and boost foreign low-frequency words. Since code-switching deals with more than a language, it is natural to exploit language identification, e.g., [17] [18] [19], or language diarization [6] to select among monolingual speech recognizers. Language identification was also employed in [12] to be combined with AM scores for better recognition performance. However, those approaches suffer from errors propagated by the language identification/diarization module to the ASR block.

In the afore-mentioned approaches, either ad-hoc acoustic and/or language models have to be built to specifically handle the CS task, or multiple language-dependent recognizers preceded by a language detection step have to be employed. In this paper, we demonstrate that leveraging existing monolingual ASR resources is possible to achieve effective intra-sentential code-switching without retraining any of the ASR models, namely the acoustic and language model, without sacrificing the recognition accuracy of the NL ASR system. We attain such a challenging goal by devising new mechanisms for foreign pronunciation generation, and LM enrichment. Specifically, we generate a high quality foreign pronunciation lexicon by obtaining the pronunciation of FL words in the NL phoneme set.
through acoustic phone decoding, and grapheme-to-phoneme conversion (G2P). Differently from [11], where phone/senone mapping and merging was the focus, we adopt data-driven techniques that learn foreign pronunciations directly from data, which in turn allows us to better deal with accented pronunciations. The experimental evidence interestingly demonstrates that data-driven acoustic phone decoding and G2P approaches perform favorably with respect to manual labeling. Moreover, we have obtained an enriched CS LM taking inspiration from [10]. Specifically, we have converted the initial NL LM into a CS LM by borrowing statistics/information from translated word pairs, which allows us to avoid LM retraining. Comparing to the state-of-the-art approach in [12], the proposed method doesn’t need to construct a new phone set and retrain the AM, and also saves the efforts to retrain the LM. The retained LM by collecting/generating new CS data as in [12] can easily harm the recognition performance on NL. Experimental evidence on introducing FL words to a NL system with vocabulary size in the hundreds of thousands demonstrate that our best system is able to provide 55.5% relative word error rate reduction (from 34.4% to 15.3%) on a code-switching testing set without harming the performance on general NL test sets.

2. Foreign Pronunciation Generation

NL refers the language whose phoneme set and AM are used in recognition. All other languages are indicated as FLs. For each FL word in a CS utterances, a native pronunciation representation in the NL’s phoneme set is generated.

2.1. Linguist Manual Labeling

Manual labeling by experts can be the most straightforward way for this kind of pronunciation generation task. Linguists with knowledge of the NL and a FL can be hired to directly produce the lexicon of FL words with NL’s phoneme set. The strength of this approach is pronunciations could be always reasonable for human perception; the shortcoming could be that linguists tend to label the FL words with the standard pronunciation, but native people always has some extent of accent when they speak foreign words in a CS scenario.

2.2. Phone Decoding

Phone decoding is a data-driven method to obtain pronunciations for the FL words. When the audio segments containing FL words, a NL ASR system can be used to decode those segments and thus obtain the possible phoneme sequences of the FL words. The audio segments mainly come from two sources: foreign people speaking FL words, and native people speaking FL words.

2.2.1. Phoneme Confusion Network

In harvesting audio segments for FL words, a particular word usually corresponds to more than one audio segment. The decoded phoneme sequences for those audio segments may vary a lot, and the process to obtain a good phoneme representation by summarizing all decoded phoneme sequences becomes crucial. In this paper, we adopt a ROVER-like [20] method based on phoneme confusion networks (CNs) to accomplish the summarization process. For example, let’s suppose that there exist three (3) audio segments containing the English word “always,” and the phone sequences generated with a Chinese ASR system are:

- OU W EI Z
- OU W I Z
- OU W EI S

Then the corresponding phoneme confusion network is displayed in Figure 1, where the numbers in parentheses represent the number of times a phoneme appears. From the phoneme confusion network in Figure 1, we can conclude that the best phoneme sequence (with most votes) for “always” is “OU W EI Z,” and the second best could either be “OU W EI S,” or “OU W I Z.” For each FL words, we can retain an N-best representation.

![Figure 1: Phoneme confusion network for the word “always”](image)

2.2.2. Phone Decoding on FL words spoken by Foreign people (PDFP)

In this paper, we suppose we have an already-trained monolingual speech recognition system for each language and there are plenty of corresponding training utterances. To harvest audio segments for foreign words, we use the FL speech recognition system to performance force alignment on its training utterances, by doing so, we can obtain the start/end time stamps of each word in those utterance. Then the audio segments containing concerned words are decoded with NL speech recognition system generating possible phoneme sequences for those words.

The advantage of this approach is that large amount of training data can be utilized to generate a lot of possible pronunciation representations and summaries them to get the best guesses, but a major concern is that those foreign words are spoken by foreign people, so to some extend, we are actually obtaining “standard” pronunciations while what we really care about is native people speaking foreign words with possible accents. To obtain such pronunciation guessing, we try to make use of the NL training data.

2.2.3. Phone Decoding on FL words spoken by Native people (PDFN)

Differently from FL training data, there are much fewer examples in NL training data that contain foreign words. Since we don’t have native pronunciation in the native phoneme set for those words, it is not possible to obtain forced-alignments and find the corresponding audio segments (for those words) as shown in Section 2.2.2. However, foreign words appearing in the NL training data are the actual CS words, and although limited amount, these words can still be fundamental to find more relative pronunciation guesses for CS speech recognition. To obtain the audio segments of those foreign words in NL training datasets, we first utilize the PDFF system (see Section 2.2.2) to obtain an initial lexicon, and we then perform forced-alignment with such an initial lexicon to find the location of those words. After finding those audio segments, we can follow Section 2.2.2 to generate the pronunciation guesses.

2.3. Grapheme-to-Phoneme Conversion

Grapheme-to-Phoneme conversion(G2P) is the process of converting the written form of a word to its pronunciation. In this paper, we use a Long Short-Term Memory (LSTM) [21] based G2P model to translate the FL words from written form to pronunciation representation in NL’s phoneme set. Our G2P model
admits an encoder-decoder architecture with attention mechanism [23] which is different from the LSTM G2P model proposed in [23]. There are two sources of data we used for the G2P model training:

(a) Standard NL lexicon containing linguist pronunciation labeling of both NL words and FL words. The amount of FL words is limited in this scenario;

(b) Phone decoding results on FL words spoken by native people (i.e., PDPN in Section 2.2.3).

The training data (b) is added for the purpose of capturing the accents of NL speakers when they speak FL words. To obtain training data (b), we went through the following steps:

1. Collect audio recordings for the 5000 most popular FL words, which are spoken by NL speakers.
2. Use G2P trained with data (a) to generate 4 pronunciations from written form for each FL word used in Step1.
3. Use a NL phone decoder to generate additional 4 pronunciations for each FL word provided the audio collected in Step1.
4. The combined 8 pronunciations from Step2 and Step3 are rescoped using the NL acoustic model, and the top 4 pronunciations with the highest acoustic model scores are retained for each FL word. Then (a) and (b) are combined to form the final training data for the LSTM G2P model training.

3. Language Model Enriching

With the FL word pronunciation problem tackled, we still have to fix the LM part to deploy a robust CS system. LM training is a crucial problem in CS speech recognition, and the chief difficulty is in finding enough intra-sentential CS training data to build a reliable CS LM. In fact, the CS phenomenon does not happen as frequently in written form. However, it should not be difficult to convince ourselves that the lack of abundant CS text material is not a real concern, since the performance of the NL ASR system would be harmed if too much CS data is used to train the LM. Therefore, we started seeking into possible ways to overcome the problem. The 224 FL words is a subset of the 1155 words which actually occur in the Chinese training data.

Language Model Enriching:

Our approach is validated using Chinese as the NL, and English as the FL.

4.1. Experimental Setup

Acoustic Model: The NL Chinese acoustic model is a Feed-Forward deep neural network (FFDNN) trained with filter bank features from 160 hours Chinese speech using cross-entropy and BMMI objective function. The FL English acoustic model utilizes similar setup.

Lexicon: Table 1 is the lexicons we obtained by methods proposed in Section 2. The 1155 FL words are selected from their appearing frequencies in the English training data and the probability occurring during Chinese-English code-switching. The 224 FL words is a subset of the 1155 words which actually occur in the Chinese training data.

Code-Switching LM: Table 2 shows the code-switching LMs obtained following Section 3. We refer to the original Chinese LM as G0, the CS LM contains the 224 English word as G1, and the CS LM contains all the 1155 words as G2.

Testing sets: There are two test sets. The code-switching test set contains 107 CS utterances. Each of the utterances contains one or more intra-sentential code-switchings. A typical one is like “我们打篮球”. The FL words included in the CS test set is mainly a subset of the 224 English words above-mentioned. The general test set contains 9677 utterances, most of which are pure Chinese utterances.

Evaluation Metric: Experimental results are reported in terms of the word error rate (WER) metric, namely each Chinese character is treated as a word in the contest of CS speech recognition.

4.2. Experimental Results

Table 3 shows the CS performance of several systems having different lexicon and LM configurations. The CS system employing the original NL lexicon, namely L0, and the original
Table 1: Lexicons used in the experimental evaluation

| Lexicons | Configurations and Methods |
|----------|-----------------------------|
| L0       | original NL lexicon (no FL words) |
| L1       | 224 FL words by linguist labeling in Section 2.2.2 |
| L2f      | 1155 FL words by PDFN in Section 2.2.3 |
| L2n      | 224 FL words by PDFN in Section 2.2.2 |
| L3a      | 1155 FL words by G2P with data (a) in Section 2.3 |
| L3ab     | 1155 FL words by G2P with data (a) and (b) in Section 2.3 |

Table 2: LMs with different FL vocabularies (see Section 3)

| LMs       | Configurations |
|-----------|----------------|
| L0+G0     | original NL LM (no FL words) |
| L1+G1     | CS LM with 224 FL words |
| L2f+G2    | CS LM with 1155 FL words |

LM, namely G0, is referred to as the baseline system. By comparing the second and third row in Table 3, we can easily argue that the proposed PDFN for generating the lexicon of FL words (see Section 2.2.2) along with enriched LM using 224 FL words (G1) delivers significant performance improvement over the baseline system. Indeed, the WER is reduced from 34.4% down to 24.3%, which is equivalent to a word error rate reduction (WERR) of 29.4%. The monolingual Chinese ASR system (baseline) cannot conversely properly recognize any foreign words, which are treated as out of vocabulary words. Moreover, we can observed that the proposed PDFN approach is equivalent, in terms of recognition performance, to the manual labeling of an expert (compare third and fourth rows). The latter might allow us to conclude that the data-driven method - without taking into account speaker’s accents yet, is comparable to an expensive human-driven solution. By taking into account the speaker’s accent using the L2n lexicon, we can further reduce the WER down to 20.7%, which represents a WERR of 39.9%, outperforming both human labeling, and the PDFN approach that tries to only generate “standard” pronunciations.

If an LSTM-based G2P approach trained on both the standard NL lexicon covering manually labeled NL and FL words (i.e., set (a) in Section 3) along with phone decoding results (i.e., set (b) in Section 2.3) is considered, a WER of 18.8% is attained, as displayed in the seventh row. By comparing the latter result with that shown in the sixth row in Table 3 which corresponds to G2P train on the set (a) only, we can see that taking speaker’s accent into account has a beneficial effect on the recognition performance. Merging together all the pronunciation guesses from different sources brings the WER down to 15.3%, as shown in the eighth row in Table 3 which accounts for a WERR of 55.5%. The latter outcome seems to imply that those pronunciation generation methods are complementary to each other.

Finally, the effect of tuning the weight-copying scale in LM enriching is given in Table 5. A scale factor is multiplied by the original NL edge’s weight before being copied in the added parallel FL edge. A value greater than 1 implies a boost of the FL edge, whereas a value smaller than 1 suppresses the FL edge. From Table 5 we can see that boosting FL edges improves the recognition performance on the CS test, but it also causes a degradation on the general test set. Suppressing FL edges won’t harm the performance on the general set but causes a degradation on the CS set. That can easily be understood by bearing in mind that errors on the CS test set are mainly caused by unrecognized FL words; therefore, better results can be obtained by boosting the FL edges. However, there are nearly no FL words in a more general test set, and that explains the drop in performance.

Table 3: WERs (in %) on CS test set by using different lexicon and LM configurations. Word error rate reductions (WERRs) are given in parentheses.

| Configuration | L0+G0 (baseline) | (L0+L2f)+G1 | (L0+L1)+G1 | (L0+L2n)+G1 | (L0+L3a)+G1 | (L0+L2f)G1 | (L0+L2n)G1+G2 | (L0+L3ab)+G1 | (L0+L3ab)+G2 |
|---------------|------------------|------------|------------|------------|------------|------------|----------------|------------|------------|
| WER on CS     | 34.4%            | 24.3%      | 24.3%      | 20.7%      | 21.6%      | 18.8%      | 18.8%          | 15.3%      | 15.3%      |

Table 4: WERs (in %) on the general test set.

| Configuration | L0+G0 (baseline) | (L0+L1+L2f)+G1 | (L0+L1+L2n)+G1 | (L0+L1+L2f)+G2 |
|---------------|------------------|----------------|----------------|---------------|
| WER on general| 14.5%            | 14.5%          | 14.6%          | 14.6%         |

5. Conclusion

In this work, we build a intra-sentential code-switching ASR prototype by leveraging existing monolingual systems without either acoustic, or language model retraining. Our approach focuses on data-driven pronunciation generation for FL words and takes into account speakers’ accent. Moreover, we also devise a simply CS LM generation approach by enriching existing monolingual LM leveraging word pairs. The significant accuracy improvement on CS test data together with retention of LM accuracy on a more general speech task highlights the effectiveness of our idea. A major limitation of the proposed approach concerns the LM enriching method, which may not handle the word reordering problem. To clear ideas, let’s consider the English word “tomorrow” that corresponds to the Chinese word “明天”. In “I will go to school tomorrow” the adverb “tomorrow” appears at the end of the sentence, but the same sentence in Chinese, namely “我明天去学校” would places “明天” in the middle of the sentence. In a CS sentence having “tomorrow” as the FL word, ‘tomorrow’ would rarely appear in the middle of the sentence, as it should in Chinese, and that may make the use of the statistics borrowed from the NL LM for the CS LM not accurate. We will try to tackle this issue by combing the proposed statistic-borrowing and the traditional data augmentation methods.
6. References

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