

# ISSUES IN RECOGNITION OF SPANISH-ACCENTED SPONTANEOUS ENGLISH

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## ABSTRACT

We describe a recognition experiment and two analytic experiments on a database of strongly Hispanic-accented English. We show the crucial importance of training on the Hispanic-accented data for acoustic model performance, and describe the tendency of Spanish-accented speakers to use longer, and presumably less-reduced, schwa vowels than native-English speakers.

## 1. INTRODUCTION

Foreign accent is a crucial problem that ASR systems must address if they are to deal with spontaneous speech. In this paper, we study the problem of recognition of English spoken by speakers with strong Spanish accents. We first show that applying a native-English-trained recognizer on Spanish-accented English data produces an unacceptable error rate. We then show that training a Spanish-accented English recognizer, even on only 20 hours of speech from only 14 Hispanic-English speakers, drops the error rate from 68.5% to 39.2%. This suggests that if sufficient amounts of accented training data are available, performance can be quite acceptable. In most cases, however, it is difficult to obtain enough training data for specific accents. The rest of this paper therefore describes two studies on the kinds of features that might be useful for adapting a native speaker ASR system to model accented data.

## 1. CORPUS

Our experiments were based on the conversational Hispanic-English spontaneous speech corpus developed at Johns Hopkins University [2]. This corpus consists of approximately 30 hours of English conversation spoken by speakers whose native language was Spanish, and who had varying degrees of Spanish accent in their English. The 18 participants (nine male, nine female) were from Central or South America, and all had lived in the United States at least one year and had a basic ability to understand, speak, and read English. The Hispanic-English corpus had been collected in a dual-recording setup. Each participant was recorded with a wide-bandwidth close-talking microphone and simultaneously with narrowband telephone channels. During the conversations, which averaged about 30 minutes each, the speakers completed four tasks: picture sequencing, story completion, and two conversational games. For the picture sequencing task, participants received

half of a randomly shuffled set of cartoon drawings and were asked to reconstruct the original narrative with their partner. For the story completion, participants were given two identical copies of a set of drawings depicting unrelated scenes from a larger narrative context and were asked to answer three questions: "What is going on here?, What happened before?, What is going to happen next?" The first conversational game, Scruples, involved reading a description of a hypothetical situation and trying to resolve the conflict or dilemma. For the second game, the speaker pairs were asked to agree on five professions to take along on a mission to Mars from a list of ten professions.

Our experiments were performed only on the wideband speech, of which we had approximately 27 hours (we did not use a small read speech part of the corpus, nor did we use the 2 to 3 hours of as-yet untranscribed data). In addition, the audio files for 2 hours of the data contained only silence, although there were corresponding transcriptions. Those silent audio files were removed from the audio corpus (leaving 25 hours), although the transcriptions were used for language model training.

These data were divided into development, training and test sets according to speaker proficiency and gender. The development and test sets each include about 2.5 hours (from two speakers in each of the two sets); while the training set contains about 150,000 words from the remaining fourteen speakers, seven male and seven female (see Table 1). Speakers had been judged on proficiency scores based on a telephone-based, automated English proficiency test [7]. We also listened to each speaker and rated their accents as heavy, mid and light. We used the accent ratings to assign one heavily accented male and one heavily accented female speaker to each of the dev and test sets.

Data	Gender	Hours	Words
Train	7 male, 7 female	20.0	154,903
Dev	1 male, 1 female	2.5	11,731
Test	1 male, 1 female	2.5	14,662

**Table 1:** Corpus Data Distribution



marked *unintelligible* or containing rare word fragments which we had not included in our training lexicon). We attempted to improve the quality of the alignments by adapting the forced aligner to each speaker using the MLLR technique, however we found that this did not result in lowered error rates in the resulting baseline system.

The final baseline system consisted of gender-dependent acoustic models for the first ASR pass. Subsequent passes utilize vocal tract length normalized models. Warping factors ranging from 0.88 to 1.12 with 0.02 increments are estimated for each training and test speaker using the hypothesis from the first-pass of the recognizer.

### 2.3. Language Model

Our Katz backoff trigram language model was estimated from the Hispanic-English corpus training set using the CMU Statistical Model Toolkit [3]. This language model had a vocabulary size of 4,123 words and a perplexity on the development set of 46.7.

## 3. ACCENT ADAPTATION: ACOUSTIC MODELS VS LANGUAGE MODEL

Speech recognition systems use both acoustic models and language models in decoding speech. Language models assign probabilities to word sequences, and acoustic models assign probabilities to words being realized as an observed acoustic feature sequence. Both types are statistical models that estimate their parameters from training data. In non-native speech, both the word sequences and the acoustic realizations of words are different than the native speech that the system was trained on. Both types of models will contribute to degraded performance. Adapting native English acoustic models to non-native English speech can significantly improve the recognition accuracy on the foreign accented speech, even with a small amount of training data. In [10] interpolating native and non-native acoustic models reduced WER from 67.3% to 45.1% for a Japanese-accented speech recognition task. We conducted a small experiment to determine the effects of using acoustic and language models trained on a different type of data than the test data. The objective in this experiment was to identify, in our foreign-accented English speech task, which factors might have more dominant influence on the system performance.

The data set was the spontaneous Hispanic-accented speech development set described earlier. Two sets of acoustic models were used, ones trained on Wall Street Journal and ones trained on the accented speech. Both training sets are wide-band speech. WSJ is speech read by native English speakers. Three language models were used, WSJ, Switchboard and a language model trained on the accented data. (Switchboard is spontaneous speech produced by native English speakers on a variety of topics [6]).

		Language Model		
		WSJ	SWB	Accent
Acoustic Model	WSJ	80.2	74.1	68.5
	Accent	56.4	46.7	39.2

**Table 4:** Word Error Rate % by Models

The results shown in Table 4 indicate clearly that using both the appropriate language model and acoustic models is important for deriving the best overall performance. As the language model becomes a better match to the development data (from read English to spontaneous English to spontaneous accented), the error rate is reduced. The accented data also matches the test domain as well as the speaking style. However, all of the evaluations done using the non-native speech acoustic models outperform all of the evaluations with WSJ models. Retraining the acoustic models on the accented data results in significantly more accurate recognition performance; e.g., 27.4% to 29.3% gain. Using a more appropriate language model has less of an effect; e.g., 5.6% to 17.2% gain. As with language models, the accented acoustic models also are appropriate to the domain as well as the speaking style (perhaps better triphone coverage for the models).

The general trend suggests that, in this foreign-accented speech, acoustic models are even less transferable than language models, and benefit more from appropriate training data. This result differs from transferring between task domains in native English recognition. It is generally found to be the case that in native English tasks acoustic models transfer well where language models do not. This result supports the result in [10] described above.

## 4. REDUCED VOWELS IN FOREIGN ACCENTED SPEECH

In our previous study [11], we found that prosodic features such as stress and pitch accent may be an important factor for the performance of an ASR system on non-native speech. Specifically, we showed that heavily-accented Spanish speakers were more likely to substitute full vowels for schwas than lightly-accented speakers. A small study of selected utterances also showed that heavily-accented speakers also had more errors in word and sentence stress than lightly-accented speakers. Our previous experiments, however, did not compare Spanish-accented speakers with native speakers. In this experiment, we follow up on our earlier finding by looking at the difference between Spanish-accented and native speech in how they deal with schwas and full vowels.

In order to determine if the results generalized to our corpus while avoiding having to hand label the stress patterns, we chose to investigate a relatively simple dependent variable: vowel durations. Our goal was to see if Spanish speakers were more likely to have full vowels (or stressed vowels) in places where native speakers had reduced vowels (schwas). We therefore looked at the average duration of schwas in the Hispanic-English corpus, and compared it to the average duration of schwas in the native-speaker Switchboard corpus. We determined the average duration of reduced vowels by performing a forced alignment to phone boundaries. Subsequently, we normalized these values by the average vowel duration in accented and native speech respectively. The ratio of these two values was calculated using equation 1 below:

$$\frac{\frac{\text{Reduced Vowel}_{\text{accented}}}{\text{Average Vowel}_{\text{accented}}}}{\frac{\text{Reduced Vowel}_{\text{native}}}{\text{Average Vowel}_{\text{native}}}} \quad (1)$$

Phoneme	Example	Normalized accented to native duration ratios
AX	alone	1.21
AXR	figure	1.14
IX	towing	1.10

**Table 5:** Normalized ratios for reduced vowels. Values greater than 1 indicate longer durations for Hispanic-accented data than for Switchboard data, after normalizing for average vowel duration.

Table 5 shows that the three schwa vowels, [ax], [axr], and [ix], are longer on average in Spanish speakers than they are in native speakers, after normalizing for the length of the average vowel in the two corpora. These results show that the Spanish-accented speakers tend not to reduce vowels as much as native American English speakers do. While we have not yet applied this result in our recognizer, our hypothesis is that modifying either the lexicon or the acoustic models to represent these longer, unreduced schwas for Spanish speakers may play a key role in dealing with accent.

Is this fact about longer, unreduced schwas a fact about Spanish-accented English or a fact about all accented speakers? Previous research suggests that this result applies only to Spanish, and that different languages have different positions along the reduction scale. For example [1] compares average word duration for Mandarin-accented and Turkish-accented speakers. They point out that while Mandarin-accented speakers had longer vowels on average than native English speakers, that Turkish speakers on average had shorter vowels. [5] points out that Korean-accented speakers emphasize durational differences between (shorter) [ih] and (longer) [iy], presumably influenced by the fact that Korean has a distinction between long and short vowels. As such, those subjects might have used duration as a more important aspect of vowel identity. Thus, while these previous studies did not directly address schwas or other reduced vowels, they do suggest that non-native speakers from different language backgrounds apply different strategies in pronouncing English vowels. This is an area that clearly calls for further investigation.

## 5. DISCUSSION

We have shown that a speech recognizer trained on native English speech performs poorly on Spanish-accented English, but that training the recognizer on Hispanic English instead drops the error rate drastically from 68.5% to 39.2%. Since accented data is not always available for training, we also performed two studies that we hope will shed light on how native-English recognizers might eventually be adapted to accented English. Our first study showed that acoustic models

are even less transferable from native to accented speech than language models, and benefit more from appropriate training data. This suggests, not surprisingly, that, when possible, acoustic training (rather than LM training) is key to better performance on accented speech. Our second study confirmed our earlier suggestions that Spanish speakers tended to use more full vowels and less schwas than native English speakers.

In our current research, we hope to apply these ideas in two ways. First, since foreign-accented acoustic data is often hard to get, we hope to try using acoustic training data in the foreign language itself. Since our first result points to the importance of acoustic training data, we hope that e.g., Spanish training data might help in building acoustic models that work well on Hispanic English. Second, we hope to build a modified Hispanic-English lexicon that directly represents the full, non-schwa vowels of the Hispanic-English speakers.

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