The Relevance of Text and Speech Features in Automatic Non-native English Accent Identification

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Abstract

This paper describes our experiments with automatically identifying native accents from speech samples of non-native English speakers using low level audio features, and n-gram features from manual transcriptions. Using a publicly available non-native speech corpus and simple audio feature representations that do not perform word/phoneme recognition, we show that it is possible to achieve close to 90% classification accuracy for this task. While character n-grams perform similar to speech features, we show that speech features are not affected by prompt variation, whereas n-grams are. Since the approach followed can be easily adapted to any language provided we have enough training data, we believe these results will provide useful insights for the development of accent recognition systems and for the study of accents in the context of language learning.

1 Introduction

Understanding and/or modeling native language (L1) influence on second (L2) language production has been a topic of research interest for a long time. Doing this with written language has several applications in domains such as customized language instruction (Lu and Ai, 2015), forensic linguistics, and stylistic studies (Argamon et al., 2009). Identifying L1 accent in L2 speech is particularly useful in applications such as personalized speech recognition and pronunciation tutoring (e.g., Eskenazi et al., 2007). It is also an important challenge to address in the age when voice-driven interfaces are commonly used by speakers with diverse accents across the world (Schuller et al., 2016). Finally, understanding L1 influence on L2, whether in written or spoken language, is also useful in understanding the process of language learning.

Considering these perspectives, there has been a surge in the research interest in this direction, as it can be seen from the recent Native Language Identification (NLI) shared tasks in the NLP community (Tetreault et al., 2013; Malmasi et al., 2017) and the Computational Paralinguistics Challenge in the Speech community (Schuller et al., 2016). There has been a lot of research into phoneme recognition based feature engineering for this task in recent past. Yet, the usefulness of low level audio features, and a comparison between audio and transcribed textual features have not been investigated systematically. Further, work on speech has been limited to proprietary datasets, often without access to the actual speech files, relying on intermediate representations.

In this background, we investigate the usefulness of easy to extract text and audio features in identifying the accent in non-native speech using a publicly available dataset. We show that:

1. audio features (without speech recognition) achieve close to 90% classification accuracy in distinguishing between 10 Asian speech accents and native English speakers.
2. n-gram feature representations from manual transcriptions achieve comparable classification performance to these low-level audio features, but are sensitive to variations in the prompts/topics.
3. audio features are not affected by prompt variation.

The rest of this paper is organized as follows. Section 2 briefly summarizes related work, and Sections 3 and 4 describe our approach and results. Section 2 surveys the related work and Section 5 summarizes the main conclusions.
2 Related Work

Automatic accent identification using non-native speech samples has seen a growing interest in the past few years (Schuller et al., 2016; Malmasi et al., 2017) and the best performing systems used features based on i-vectors, and combinations of different word level features along with i-vectors. In comparison, there is not much work on how low level audio feature representations perform against features requiring speech recognition.

Related research in NLI for written texts explored a range of languages, feature combinations and model ensembles in the past 5 years (e.g., Tetreault et al., 2013; Malmasi, 2016; Bich, 2017; Malmasi and Dras, 2017). In general, word and character n-gram features have given the best performing results for this task although these textual features were also shown to be sensitive to the training data (Malmasi and Dras, 2015). The NLI shared task in 2017 had both written and spoken tasks (Malmasi et al., 2017), in which manual transcriptions of speech files were provided along with i-vectors (instead of original audios). While i-vectors were shown to be useful for this task, the n-gram features from manual transcriptions were shown to complement these features. However, manual transcriptions are unavailable in real world, beyond the experimental datasets. Yet, assuming the presence of automatic transcriptions will raise the question - "why can’t we use ngram features from such transcriptions, as they perform the best with written language?"

In this background, we explore the following questions in this paper:

1. How far can we go without speech recognition/transcription for accent identification?
2. Can speech features work across prompts, unlike text ngram features?

3 Approach

Corpus: We used the speech part of the International Corpus Network of Asian Learners of English (ICNALE), which is a publicly and freely available corpus non-native writing and speech (Ishikawa, 2014). It contains 4400 English speech samples (approximately 1 minute in duration each), recorded in response to two prompts, along with plain text transcriptions. The data consists of speakers from 10 Asian countries and a sample of native English speakers. While there are other accent corpora such as the CSLU Foreign Accented English (Lander, 2007) and the speech accents archive, we did not find them suitable for this task. The CSLU corpus had only one prompt, and no transcriptions, and the GMU corpus is not spontaneous speech. ICNALE corpus was used in the recent past (Nisioi, 2016) in a similar task, to perform pair-wise NLI. The audio files in ICNALE underwent a morphing procedure for privacy reasons, to protect anonymity of participants. This involved altering the pitch and format to perform speaker normalization. Table 1 shows the class distribution in the corpus.

| Language       | Num. Audio files |
|----------------|------------------|
| Native English (ENS) | 600              |
| Hongkong English (HKG) | 200              |
| Pakistan (PAK)     | 400              |
| Philippines (PHL)  | 400              |
| Singapore (SIN)    | 200              |
| China (CHN)        | 600              |
| Indonesia (IDN)    | 400              |
| Japan (JPN)        | 600              |
| Korea (KOR)        | 400              |
| Thailand (THA)     | 200              |
| Taiwan (TWN)       | 400              |

Table 1: Composition of ICNALE spoken Corpus.

3.1 Features

We used two kinds of feature representations, one for audio and one for transcriptions. For the audio features, we employed the low level acoustic descriptors baseline from INTERSPEECH ComParE challenges (Schuller et al., 2013), extracted using OpenSmile (Eyben et al., 2010). This contains 6373 static features describing signal properties such as amplitude statistics, signal energy features, and features related to magnitude spectra, auto-correlation and cepstral characteristics (Eyben, 2015). These low-level features were known to be useful for performing a range of audio and music classification tasks in the past, and was also used as a baseline feature set in the first speech native language identification challenge. From the transcriptions, we extracted word and character n-gram features considering up to 3-grams for words and 10-grams for characters. We extracted char-

\footnote{http://accent.gmu.edu/}

\footnote{The morphing software is publicly available on the corpus website}
acter n-grams both with and without considering word boundaries.

### 3.2 Model selection and evaluation

The dataset gives us a 11-class classification problem, and we explored a range of standard supervised learning algorithms for this purpose. Since the class distribution is unbalanced, we also experimented with oversampling the classes with less number of examples using SMOTE (Chawla et al., 2002) which creates additional synthetic examples for minority classes to balance the class distribution in training data. Model selection was done using cross-validation (CV) when the entire dataset is used, and by comparing results on test-set for cross prompt evaluation. Due to space constraints, we report only classification accuracy as our evaluation measure, as the manual inspection of confusion matrices did not show any apparent bias towards any class. The experiments were done using WEKA and scikit-learn (Pedregosa et al., 2011; Buitinck et al., 2013).

### 4 Experiments and Results

#### With Speech Features: We trained classification models with all the 6373 audio features and with manual and automatic feature selection. Formant frequency features were shown to be useful for accent identification in early research (Kat and Fung, 1999). Others such as voicing features are meant to capture prosody in speech, and features based on MFCCs, and auditory spectrum features are used in speech recognition. So, these features can be considered as having some theoretical relevance for this task, compared to other features based on signal energy and other properties. Hence, we trained classifiers with these subsets. Table 2 shows the results for these experimental settings, with Sequential Minimal Optimization (SMO), which was the best performing classifier for these features in our experiments. The model with all the features, along with SMOTE oversampling, gives the best classification accuracy of 90.8% for these features. Smaller feature subsets did not perform well, which indicates that the other audio signal features we excluded could be playing an important role in performing the classification. So, we explored automatic feature selection using three commonly used methods: Information gain, Chi-square, and ReliefF (Kira and Rendell, 1992), changing the number of top-N best features chosen (N=100 to 6000). Figure 1 shows a summary of these models, with cross-validation on the original training data (without SMOTE).

#### With Textual Features: Aside from speech based features, we trained classification models with word and character n-gram features from the transcriptions. Table 3 summarizes the results with these features with Multinomial Logistic Regression (MLR), which gave the best results for these features.

From Table 3, we observe that n-gram features

| Description       | num. feat. | Accuracy |
|-------------------|------------|----------|
| all (1)           | 6373       | 77.9%    |
| Formant           | 83         | 45.2%    |
| Voicing           | 78         | 42.0%    |
| MFCCs             | 1400       | 69.4%    |
| Aud. spec.        | 100        | 51.0%    |
| all feat. + SMOTE (2) | 6373     | 90.8%    |

Table 2: Accent identification with Speech features

![Figure 1: Feature selection with speech features](image)

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3Weighted F1 and other measures can be added, if necessary, in the final version of the paper.
Features | Accuracy
---|---
Word n-grams (3) | 83.8%
Char n-grams across word-boundaries (4) | 88.3%
Char n-grams, w/o word boundaries (5) | 84.7%
(3) + (4) | 88.9%

Table 3: Accent identification with n-grams from transcriptions

with minimal pre-processing seem to be extremely predictive of native accents. These results seem in contrast to the results from NLI Shared Task-2017 (Malmasi et al., 2017), where the word/character level features did not perform well as a stand-alone feature set with Speech data, but improved the performance when added to i-vector features, with the best performing system achieving an accuracy of 87.5% combining i-vectors and transcription features. However, it is difficult to compare these results as they come from different datasets.

In our experiments, low level speech features are clearly doing well by themselves, achieving 90% accuracy with feature selection. While they have only been used as baseline in contemporary approaches, there is also no systematic study on how far can we go with them without training speech recognition models. This paper shows that systematic feature selection may result in high accuracies for this task even with these baseline features.

### 4.1 Prompt Specificity in Accent Identification

In order to study the variation due to prompt, we split the dataset in to two parts. Since each participant responded to both the prompts in the corpus, the distribution of L1s in the training and test corpus remained the same. Table 4 shows a summary of the results for different experimental settings (from Tables 2 and 3), for 10-fold CV per prompt, and evaluation on the other prompt. The row best indicates the best performing feature configuration from Figure 1 (3500 features selected using information gain). As mentioned earlier, results for ngram features are with MLR and results for speech features are with SMO. Speech and text features were not combined in this paper as the text features are not shown to generalize across prompts.

| set. | P1-CV | Train:P1, Test:P2 | P2-CV | Train:P2, Test:P1 |
|---|---|---|---|---|
| (1) | 70.6% | 74.9% | 71.3% | 72.8% |
| (2) | 88.4% | 75.3% | 88.2% | 73.04% |
| (3) | 83.1% | 52.6% | 81.95% | 41.8% |
| (4) | 88.2% | 58.2% | 87.95% | 57.6% |
| (5) | 85.4% | 44.95% | 82.95% | 38.3% |
| (3)+(4) | 88.81% | 56.1% | 88% | 52.2% |

**best** | 83.1% | 87.3% | 83.9% | 85.8%

Table 4: Accuracy for prompt specific experiments

Clearly, there is a huge drop in accuracy from one prompt to another for the n-gram features, sometimes as much as 40%. While over-sampling resulted in a increased classification accuracy in the prompt specific evaluation for speech features, it did not do improve cross-prompt evaluation. Cross-prompt evaluation results being better than same prompt evaluation for (1) and best settings is primarily due to the fact that there is a +/- 5% variation between CV folds, and we report only the average. Overall, these results lead us to a conclusion that employing low level audio features, without speech recognition and without transcriptions can possibly achieve generalizable speech accent identification.

### 5 Conclusion

Our experiments show that speech features from low level audio representations achieve over 90% classification accuracy for a 11-class native accent identification problem, after performing feature selection. Further, the results indicate that these features can be potentially prompt independent, which has been a consistent issue regarding the generalizability of NLI models in the past. These encouraging results lead us to several interesting problems to explore in accent identification. Immediate extensions include comparing this with i-vector features, and exploring the usefulness of neural network architectures for the task. Additionally, since the approach does not have language specific components in the pipeline, we plan to replicate the experiments with L2 German and Arabic for which such corpora are freely available. Another interesting dimension to explore is to use text features from automatic transcriptions, as the transcription errors perhaps capture accent differences while manual transcriptions cannot.
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