

AISHELL-1: AN OPEN-SOURCE MANDARIN SPEECH CORPUS AND A SPEECH RECOGNITION BASELINE

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ABSTRACT

An open-source Mandarin speech corpus called AISHELL-1 is released. It is by far the largest corpus which is suitable for conducting the speech recognition research and building speech recognition systems for Mandarin. The recording procedure, including audio capturing devices and environments are presented in details. The preparation of the related resources, including transcriptions and lexicon are described. The corpus is released with a Kaldi recipe. Experimental results implies that the quality of audio recordings and transcriptions are promising.

Index Terms— Speech Recognition, Mandarin Corpus, Open-Source Data

1. INTRODUCTION

Automatic Speech Recognition(ASR) has been an active research topic for several decades. Most state-of-the-art ASR systems benefit from powerful statistical models, such as Gaussian Mixture Models(GMM), Hidden Markov Models(HMM) and Deep Neural Networks(DNN) [1]. These statistical frameworks often require a large amount of high quality data. Luckily, along with the wide adoption of smart phones, and the emerging market of various smart devices, real user data are generated world-wide and everyday, hence collecting data becomes easier than ever before. Combined with sufficient amount of real data and supervised-training, statistical approach achieves great success all over the speech industry [2].

However, for legal and commercial reasons, most companies are not willing to share their data with the public: large industrial datasets are often inaccessible for academic community, which leads to a divergence between research and industry. On one hand, researchers are interested in fundamental problems such as designing new model structures or beating over-fitting under limited data. Such innovations and tricks in academic papers sometimes are proven to be not effective when the dataset gets much larger, different scales of

data lead to different stories. On the other hand, industrial developers are more concerned about building products and infrastructures that can quickly accumulate real user data, then feedback collected data into simple algorithms such as logistic regression and deep learning.

In ASR community, open-slr project is established to alleviate this problem¹. For English ASR, industrial-sized datasets such as Ted-Lium [3] and LibriSpeech [4] offer open platforms, for both researchers and industrial developers, to experiment and to compare system performances. Unfortunately, for Chinese ASR, the only open-source corpus is THCHS30, released by Tsinghua University, containing 50 speakers, and around 30 hours mandarin speech data [5]. Generally speaking, Mandarin ASR systems based on small dataset like THCHS30 are not expected to perform well.

In this paper, we present AISHELL-1 corpus. To authors' limited knowledge, AISHELL-1 is by far the largest open-source Mandarin ASR corpus. It is released by Beijing Shell-Shell Company², containing 400 speakers and over 170 hours of Mandarin speech data. More importantly, it is publicly available and is under Apache 2.0 license. This paper is organized as below. Section 2 presents the recording procedure, including audio capturing devices and environments. Section 3 describes the preparation of the related resources, including transcriptions and lexicon. Section 4 explains the final structure of released corpus resources. In Section 5, a "drop-in and run" Kaldi recipe is provided as a Mandarin ASR system baseline.

2. CORPUS PROFILE

AISHELL-1 is a subset of the AISHELL-ASR0009 corpus, which is a 500 hours multi-channel mandarin speech corpus designed for various speech/speaker processing tasks. Speech utterances are recorded via there categories of devices in parallel:

1. Microphone: a high fidelity AT2035 microphone with a Roland-R44 recorder working at 44.1 kHz, 16-bit.

*The authors performed the work while off duty.

¹<http://www.openslr.org>

²<http://www.aishelltech.com>

2. Android phone: including Samsung NOTE 4, Samsung S6, OPPO A33, OPPO A95s and Honor 6X, working at 16 kHz, 16-bit.
3. iPhone: including iPhone 5c, 6c and 6s, working at 16 kHz, 16-bit.

The relative position of speaker and devices are shown as Figure 1. The AISHELL-1 database choose high fidelity microphone audio data and re-sampled to 16 kHz, 16-bit WAV format, which is the mainstream setup for commercial products.

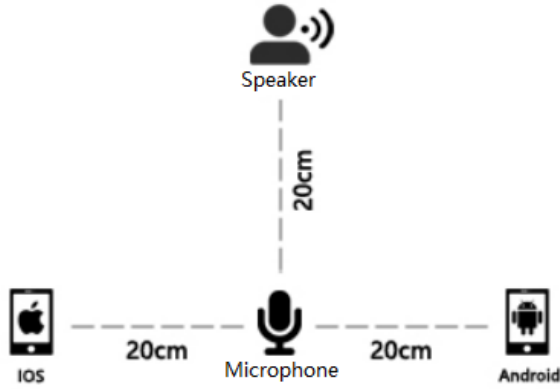


Fig. 1. Recording setup

There are 400 participants in the recording, and speakers gender, accent, age and birth-place are recorded as metadata. The gender is balanced with 47% male and 53% female. As shown in Table 1, about 80 percent, of the speakers are of age 16 to 25. Most speakers come from Northern area of China, detailed distribution is shown in Table 2. The entire corpus includes training, development and test sets, without speaker overlapping. The details are presented in Section 4.

Table 1. Speaker age and gender information

| Age Range | #Speakers | Male | Female |
|-------------|-----------|------|--------|
| 16 - 25 yrs | 316 | 140 | 176 |
| 26 - 40 yrs | 71 | 36 | 35 |
| > 40 yrs | 13 | 10 | 3 |

3. TRANSCRIPTION AND LEXICON

The AISHELL-ASR0009 corpus covers common applications such as smart home, autonomous driving, and the raw text transcriptions are chosen from in 11 domains, as shown in Table 3, including 500k commonly used sentences. The released AISHELL-1 corpus covers 5 of them: “Finance”,

Table 2. Speaker accent information

| Accent Area | #Speakers |
|--------------------------|-----------|
| North | 333 |
| South | 38 |
| Guangdong-Guangxi-Fujian | 18 |
| Other | 11 |

“Science and Technology”, “Sports”, “Entertainments” and “News”. Raw texts are manually filtered to eliminate improper contents involving sensitive political issues, user privacy, pornography, violence, etc.. Symbols such as <, >, [,], ~, /, \, =, etc., are removed. Long sentences over 25 words are deleted. All text files are encoded in UTF8.

Table 3. Topics of text

| Topic | #Sentences |
|----------------------------------|------------|
| Smart Home Voice Control | 5 |
| POI (Geographic Information) | 30 |
| Music (Voice Control) | 46 |
| Digital Sequence (Voice Control) | 29 |
| TV Play and Film Names | 10 |
| Finance | 132 |
| Science and Technology | 85 |
| Sports | 66 |
| Entertainments | 27 |
| News | 66 |
| English Spelling | 4 |

In quality checking stage:

1. data annotators are asked to transcribe speech data, utterances with inconsistent raw text and transcription are removed.
2. Text normalization(TN) is carefully applied towards english words, numbers, name, place, organization, street, shop, brand, examples are:
 - 123 are normalized to yi1 er4 san1 .
 - All the letters or words contained in the URL are capitalized. For example, the pronunciation content for the “www.abc.com”, are normalized to “san1 W dian3 A B C dian3 com”.
 - English abbreviations such as CEO, CCTV are presented in uppercase.
3. utterances containing obvious mis-pronunciations are removed.

Besides, A Chinese lexicon is provided in AISHELL-1 corpus. The lexicon is derived from open source lexicon³ and

³<https://www.mdbg.net/chinese/dictionary?page=cc-cedict>

covers most of the commonly used Chinese words and characters. Pronunciations are presented in initial-final syllable.

4. DATA STRUCTURE

The corpus includes training set, development set and test sets. Training set contains 120,098 utterances from 340 speakers; development set contains 14,326 utterance from the 40 speakers; Test set contains 7,176 utterances from 20 speakers. For each speaker, around 360 utterances (about 26 minutes of speech) are released. Table 4 provides a summary of all subsets in the corpus.

Table 4. Data structure

| Subset | Duration(hrs) | #Male | #Female |
|-------------|---------------|-------|---------|
| Training | 150 | 161 | 179 |
| Development | 10 | 12 | 28 |
| Test | 5 | 13 | 7 |

5. SPEECH RECOGNITION BASELINE

In this section we present a speech recognition baseline released with the corpus as a Kaldi recipe⁴. The purpose of the recipe is to demonstrate that this corpus is a reliable database to conduct Mandarin speech recognition.

5.1. Experimental setup

The acoustic model (AM) of the ASR system was built largely following the Kaldi HKUST recipe⁵. The training started from building an initial Gaussian mixture model-hidden Markov model (GMM-HMM) system. The acoustic feature consists of two parts, i.e. 13-dimensional Mel frequency cepstral coefficients (MFCC) and 3-dimensional pitch features. The selected pitch features are Probability of Voicing (POV) feature obtained from Normalized Cross Correlation Function (NCCF), log pitch with POV-weighted mean subtraction over 1.5 second windows, and delta pitch feature computed on raw log pitch [6]. Mean normalization and double deltas are applied on the above features before feeding into the training pipeline. The GMM-HMM training pipeline is built using tone-dependent decision trees, meaning that phones with different tonalities as defined in the lexicon are not clustered together. Maximum likelihood linear transform (MLLT) and speaker adaptive training (SAT) are applied in the training considering that there is a fair amount of training data for each of the speakers. The resulting GMM-HMM model has 3, 027 physical p.d.f.s.

⁴<https://github.com/kaldi-asr/kaldi/tree/master/egs/aishell>

⁵<https://github.com/kaldi-asr/kaldi/tree/master/egs/hkust>

High resolutional (40-dimensional) MFCC and 3-dimensional pitch features are used in the training of DNN-based acoustic models. Two techniques are applied in DNN training to enhance acoustic features. The first one is audio augmentation [7]. The speaking speed of the training set is perturbed using factor of 0.9 and 1.1, resulting in a three times larger training set. Besides, the volume of the training data is perturbed randomly. This technique helps make the DNN model more robust to the tempo and volume invariances of the testing data. The second technique is i-Vector based DNN adaptation, which is used to replace mean normalization and double deltas [8]. A quarter of the training data is used to compute a PCA transform and to train a universal background model. Then all the training data is used to train the i-Vector extractor. Only the MFCCs are used in the i-Vector extractor training. The estimated i-Vector features are of 100-dimensional.

The DNN model we used was the time delay neural network (TDNN) [9]. It contained 6 hidden layers, and the activation function was ReLU [10]. The natural stochastic gradient descent (NSGD) algorithm was employed to train the TDNN [11]. The input feature involved high resolutional MFCC, pitch features, and the i-Vector feature. A symmetric 4-frame window is applied on MFCC and pitch features to splice neighboring frames. The output layer consisted of 3, 027 units, equal to the total number of p.d.f.s in the GMM-HMM model that was trained to bootstrap the TDNN model.

Lattice-free MMI training is employed for comparison with conventional GMM-HMM bootstrapped system [12]. The left-biphone configuration is used and the resulting number of targets for DNN is 4, 476. The DNN model used in LFMMI training is also TDNN with 6 hidden layers, and configured to be of the similar number of parameters as the DNN-HMM model.

5.2. Language model

A trigram language model is trained on 1.3 million words of the training transcripts. Out-of-vocabulary (OOV) words are mapped into <SPOKEN_NOISE>. The language model is trained using interpolated Kneser-Ney smoothing and the final model has 137, 076 unigrams, 438, 252 bigrams and 100, 860 trigrams.

5.3. Results

The results are presented in term of character error rate (CER). The base results of GMM-HMM, TDNN-HMM and LFMMI models are shown in Table 5. The performances on developing set are better than the testing set. The performance of LFMMI model is significantly better than TDNN-HMM, indicating that the corpus has a high transcription quality. Audio quality can be reflected by the performance on totally difference data from the training set. Thus we evaluate the models on the mobile recording channel and THCHS30 testing set.

Table 5. Baseline results

| Model | CER of dev | CER of test |
|----------|------------|-------------|
| MLLT+SAT | 10.43% | 12.23% |
| TDNN-HMM | 7.23% | 8.42% |
| LFMMI | 6.44% | 7.62% |

5.3.1. Decoding the mobile recordings

The parallel testing recordings using Android and iOS devices are selected from the AISHELL-ASR0009 corpus, and they are used to evaluate the performance of the AISHELL-1 model on less fidelity devices. Results are shown in Table 6. **Device mismatch results in significant performance loss.** However, stronger acoustic models improves the performance on such less fidelity devices.

Table 6. Mobile recording results

| Model | CER of iOS | CER of Android |
|----------|------------|----------------|
| MLLT+SAT | 12.64% | 11.88% |
| TDNN-HMM | 12.42% | 10.81% |
| LFMMI | 10.90% | 10.09% |

5.3.2. Decoding the THCHS30 test set

The performance of AISHELL-1 model on testing cases of an unrelated language model domain than the training set reflects the overall quality of the corpus. Table 7 shows that stronger acoustic models performs better on an unrelated domain, indicating that the corpus is phonetically covered and an adapted language model will fill the performance gap.

Table 7. THCHS30 testing set results

| Model | CER |
|----------|--------|
| MLLT+SAT | 32.23% |
| TDNN-HMM | 28.15% |
| LFMMI | 25.00% |

6. CONCLUSIONS

An open-source Mandarin corpus is released⁶. To our best knowledge, it is the largest academically free data set for Mandarin speech recognition tasks. Experimental results are presented using the Kaldi recipe published along with the corpus. The audio and transcription qualities are promising for constructing speech recognition systems for Mandarin.

7. REFERENCES

- [1] Geoffrey E Hinton, Li Deng, Dong Yu, George E Dahl, Abdelrahman Mohamed, Navdeep Jaitly, Andrew W Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N Sainath, et al., “Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups,” *IEEE Signal Processing Magazine*, vol. 29, no. 6, pp. 82–97, 2012.
- [2] Awni Y. Hannun, Carl Case, Jared Casper, Bryan Catanzaro, Greg Diamos, Erich Elsen, Ryan Prenger, Sanjeev Satheesh, Shubho Sengupta, Adam Coates, and Andrew Y. Ng, “Deep Speech: Scaling up end-to-end speech recognition,” *CoRR*, vol. abs/1412.5567, 2014.
- [3] P. Deleglise A. Rousseau and Y. Esteve, “TED-LIUM: an automatic speech recognition dedicated corpus,” in *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC’12)*, May 2012.
- [4] V. Panayotov, G. Chen, D. Povey, and S. Khudanpur, “Librispeech: An ASR corpus based on public domain audio books,” in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, April 2015, pp. 5206–5210.
- [5] Zhiyong Zhang Dong Wang, Xuwei Zhang, “THCHS-30 : A Free Chinese Speech Corpus,” 2015.
- [6] P. Ghahremani, B. BabaAli, D. Povey, K. Riedhammer, J. Trmal, and S. Khudanpur, “A pitch extraction algorithm tuned for automatic speech recognition,” in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, May 2014, pp. 2494–2498.
- [7] Tom Ko, Vijayaditya Peddinti, Daniel Povey, and Sanjeev Khudanpur, “Audio Augmentation for Speech Recognition,” in *Proceedings of Interspeech*. 2015, ISCA.
- [8] M. Karafiat, L. Burget, P. Matejka, O. Glembek, and J. Cernocky, “iVector-based discriminative adaptation for automatic speech recognition,” in *2011 IEEE Workshop on Automatic Speech Recognition Understanding*, Dec 2011, pp. 152–157.
- [9] Vijayaditya Peddinti, Daniel Povey, and Sanjeev Khudanpur, “A time delay neural network architecture for efficient modeling of long temporal contexts,” in *Proceedings of Interspeech*. 2015, ISCA.
- [10] M. D. Zeiler, M. Ranzato, R. Monga, M. Mao, K. Yang, Q. V. Le, P. Nguyen, A. Senior, V. Vanhoucke, J. Dean, and G. E. Hinton, “On rectified linear units for speech

⁶<http://www.openslr.org/33/>

processing,” in *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, May 2013, pp. 3517–3521.

- [11] Daniel Povey, Xiaohui Zhang, and Sanjeev Khudanpur, “Parallel training of Deep Neural Networks with Natural Gradient and Parameter Averaging,” *CoRR*, vol. abs/1410.7455, 2014.
- [12] Daniel Povey, Vijayaditya Peddinti, Daniel Galvez, Pegah Ghahrmani, Vimal Manohar, Yiming Wang, Xingyu Na, and Sanjeev Khudanpur, “Purely sequence-trained neural networks for ASR based on lattice-free MMI,” in *Proceedings of Interspeech*. 2016, ISCA.