JTUBESPEECH: CORPUS OF JAPANESE SPEECH COLLECTED FROM YOUTUBE FOR SPEECH RECOGNITION AND SPEAKER VERIFICATION

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ABSTRACT

In this paper, we construct a new Japanese speech corpus called “JTubespeech.” Although recent end-to-end learning requires large-size speech corpora, open-sourced such corpora for languages other than English have not yet been established. In this paper, we describe the construction of a corpus from YouTube videos and subtitles for speech recognition and speaker verification. Our method can automatically filter the videos and subtitles with almost no language-dependent processes. We consistently employ Connectionist Temporal Classification (CTC)-based techniques for automatic speech recognition (ASR) and a speaker variation-based method for automatic speaker verification (ASV). We build 1) a large-scale Japanese ASR benchmark with more than 1,300 hours of data and 2) 900 hours of data for Japanese ASV.

Index Terms— automatic speech recognition, automatic speaker verification, speech corpus, YouTube

1. INTRODUCTION

Powered by the development of deep learning, significant progress has been made on various speech recognition tasks, e.g., automatic speech recognition (ASR) [3]–[5] and automatic speaker verification (ASV) [6], [7]. Due to data hungeriness of deep learning, massive-size speech corpora have been constructed and published. It is desirable to build and publish speech corpora of all languages for decentralizing the speech technologies. However, corpora in languages other than English are very poor. For example, while several thousands of hours of corpora have been published in English and Chinese [8]–[14], similar-size corpora are very limited for other languages.

Japanese, the target language in this paper, is also this example. The CSJ corpus [15] is the most frequently used corpus for Japanese ASR, but its size is relatively small (600 hours) compared to modern English corpora such as Common Voice [10] (1,100 hours). Also, the modern size of ASV corpora is more than 1,000 hours [14], [16], but there is no open-sourced corpus for Japanese ASV.

To construct a large-scale corpus, several studies have collected text-audio pairs from videos [11], [15]–[18]. For example, YouTube provides videos in diverse genres, recording environments, speakers, and language accents. There is no doubt that such in-the-wild data is useful for wide purpose of modern speech technology. Chen [19] proposed a strategy to collect English videos for ASR use. Also, Fan [14] manually selected Chinese celebrities and extracted videos for ASV use. Unlike these methods that require language-dependent and manual processes, this paper aims to develop a corpus with almost no language-dependent and no manual processes. The establishment of this method will be useful for building corpora of many languages, not limited to English and Chinese.

In this paper, we propose a mostly language-independent strategy to construct a speech corpus for both ASR and ASV, and then construct a Japanese speech corpus “JTubespeech” by using the proposed method. We first crawl YouTube in order to generate candidate audio-text pair data. For ASR, the subtitles are aligned to the audio using a CTC-based ASR model using CTC segmentation [20]. This method calculates a confidence score to filter the audio-text pair [20]–[22]. Unlike the conventional hidden Markov model (HMM) based cleaning [23], [24], this method does not require any language-dependent pre-processing thanks to the end-to-end framework. Also, for ASV, the audio can be filtered by calculating variation of speaker representation within a video. This paper applies the above techniques to a Japanese corpus as a case study. Experimental evaluation demonstrates 1) we designed a new Japanese ASR benchmark with more than 1,300 hours of training data and the official test sets, and 2) we also constructed 900 hours of Japanese ASV corpus. The contributions of this work are as follows:

- We construct a new modern-size corpus for Japanese ASR and ASV from YouTube videos. The video list is open-sourced in our project page ³.
- Our process is applicable to many languages with high reproducibility. The repository also contains the script, which has been extended to support multiple languages for the data collection.

2. CORPUS CONSTRUCTION

All of our steps are performed with minimal language-dependent processing. Figure 1 shows the procedure.

https://github.com/sarulab-speech/jtubespeech
2.1. Data collection

Creating search terms. The first step is to create search terms to be entered into the video search engine. We extract the target language’s words with hyperlinks from HTML files of Wikipedia articles. Unlike Gigaspeech [19], categories are not specified, i.e., all articles are used. Also, we extract “sudden-rise search terms” in the past few years from Google Trends.

Obtaining video IDs that have subtitles. Next, we retrieve video IDs that have subtitles. Entering a search word into the video search engine, we obtain a list of video ID candidates. Then, for each video, we retrieve whether the video has subtitles. In this paper, we use only manual subtitles but also make the list for automatic (i.e., machine-generated) subtitles.

Downloading audio and caption. Finally, we download the audio and manual subtitles from videos. Since the number of channels and sampling frequency of the audio file varies from video to video, we reformat the audio to 16 kHz-sampled monaural WAV format.

2.2. Specific cleansing for speech recognition

The obtained audio data were already annotated with subtitles including timings. This dataset still included many bad samples, e.g., unspoken subtitles, English audio with Japanese subtitles, and other variations of audio–text mismatches. To sort-out these bad samples, we calculated a score of how well the audio segment fits to the subtitle and then filtered the utterances based on their score. Furthermore, as many subtitle timings were inaccurate, we fully re-aligned the subtitles to the audio. To calculate a score and to re-align the subtitles to the audio, we use CTC segmentation [20] as an alignment tool. CTC segmentation utilizes CTC log-posteriors to determine utterance timings in the audio given a ground-truth text.

Text pre-processing. We apply minimal text pre-processing so that the ground truth text obtained from subtitles is composed of characters or tokens in the model dictionary. Numbers are replaced with their spoken equivalent using the num2words Python library [26]. UTF-16 characters are mapped to the Japanese character set. Automated subtitles are detected and filtered out based on the average relative Levenshtein distance between subtitles.

Alignment. The onset and offset timings of an utterance are then estimated in three steps: (1) In a forward pass, transition probabilities are mapped into a trellis diagram of the ground-truth token sequence over all time steps. (2) Backtracking starts from the most probable timing of the last character and then determines the most probable path through the trellis. (3) A confidence score is derived for each utterance from the per-token probabilities in the trellis. The score is determined by the L consecutive CTC output frames of the utterance with the lowest token probabilities; we chose \( L = 30 \) that relates to approximately 1s of audio. For a more in-depth description, readers could refer to [20]. We apply one further modification that helps with the alignment of fragmented subtitle text: In the original publication, the algorithm was configured to skip preambles by setting transition cost to zero for the token that marks the start of the first utterance. We extended this in our setup to all utterances in order to skip any unrelated audio segments.

CTC scoring. We also calculate a CTC score for each audio-text pair from its YouTube timings instead of fully aligning the subtitles to audio. For this, the audio segment to each subtitle is cut out to then derive its confidence score as described above.

Cleaning. Bad samples are then eliminated based on this confidence score. The confidence score provides an estimated log-space probability of how well the subtitles fit the audio data; this value is mainly influenced by the quality of ASR models, input data, and data pre-processing. Note that a score threshold \( \theta \) of \(-0.3\), used in one of our experiments, can be interpreted as a production probability of at least 75% each second.

2.3. Specific cleansing for speaker verification

Unlike an ASR corpus, ASV requires high-quality speaker labels. Therefore, we propose an unsupervised method for only extracting monologue videos (i.e., single-speaker videos) from the obtained videos. Furthermore, we remove videos with text-to-speech (TTS) voices, which have different characteristics from natural speech.

Removing non-speech and too-short videos. First, we delete videos without speech. Unlike the corpus for ASR, there is no need to align subtitle and speech. Therefore, we simply use voice activity detection (VAD) here. We applied VAD to sections trimmed out based on the subtitles and used only sections mainly consisting of speech. Also, too-short videos are deleted. This is for robustly calculating the intra-video statistics described below.

Evaluating intra-video variation in speaker space. To extract single-speaker videos, we compute the speaker variability in the video. Figure 2 illustrates the concept. We use the d-vector [6], a deep learning-based speaker representation, which is extracted using pre-trained models. The d-vector is first calculated for each utterance. Then, the variance of the d-vectors is calculated within the video. We expect that the variance of TTS voices becomes smaller than the single-speaker voices because the TTS voice has no fluctuation among utterances. Also, if the different speakers’ voices are contaminated (i.e., multi-speaker video), the variance will become larger than the single-speaker video. Therefore, we can eliminate TTS videos and multi-speaker videos by setting the appropriate threshold to the variance. For implementation, the d-vector is reduced to a lower dimension by t-SNE [27], and the determinant of
Table 1. Results of data collection. Videos with automatic subtitles are not used in this paper, but the video ID is also opensourced.

| #search-terms | #videos found in the search | #videos with manual subtitles | (#videos with auto subtitles) |
|----------------|-----------------------------|------------------------------|-------------------------------|
| 2.34M terms    | 11.9M videos                | 0.11M videos                 | 4.96M videos                  |

Table 2. Comparison of speech corpora of Japanese (upper half) and other rich-resource languages (lower half).

| Lang. | Task | Corpus            | Open-source | Duration |
|-------|------|-------------------|-------------|----------|
| Ja    | ASR/ASV | JNAS [28]         | No          | 90       |
| Ja    | ASR   | CSJ [15]          | No          | 600      |
| Ja    | ASR   | LaboroTVspeech [29] | Yes         | 2,000    |
| Ja    | ASR   | Common Voice [10] | Yes         | 2        |
| Ja    | ASR   | Liveness [30]     | No          | 4        |
| Ja    | ASR/ASV | JTubeSpeech (ours) | Yes        | 1,300/900 |
| En    | ASR   | LibriSpeech [9]   | Yes         | 982      |
| En    | ASR   | Common Voice [10] | Yes         | 1,100    |
| En    | ASR   | SPGISpeech [11]   | Yes         | 5,000    |
| En    | ASR   | GigaSpeech [17]   | Yes         | 10,000   |
| En    | ASR   | VoxCeleb [17]     | Yes         | 2,800    |
| Zh    | ASR   | Common Voice [10] | Yes         | 12       |
| Zh    | ASR   | AISHELL-2 [31]    | Yes         | 1,000    |
| Zh    | ASR   | CN-Celeb [14]     | Yes         | 1,000    |

3. EXPERIMENTAL EVALUATION

3.1. Evaluation in data collection

The period of data collection was between February and April of 2021. From the data collection results listed in Table 1, we can describe (1) 5,000 videos are found for each search term and (2) 0.92% of videos have manual subtitles, and 41.7% have automatic subtitles. In the end, we obtained approximately 10,000 hours of speech data from 110,000 YouTube videos.

Table 2 shows a comparison with the existing corpus. The duration of our corpus is a subset used in the ASR or ASV experiments described below. Among ASR corpora, our corpus is similar in size to LaboroTVspeech (Ja) [29] and Common Voice (En) [10]. Also, among ASV corpora, it is the first open-source Japanese corpus and is similar in size to CN-Celeb (Zh) [14].

3.2. Evaluation in speech recognition

Data cleaning. The most important data pre-processing is to prune utterances that have the wrong transcription and fix the incorrect timing. We consistently employed CTC segmentation and CTC scoring, as described in Section 2.3. We used a pre-trained CTC model based on the ESPnet LaboroTVspeech [29] recipe [32]. Table 3 summarizes the statistic of the various training and test sets.

As a pilot study, we used two subsets of our corpus: (1) "single speaker" (or "ss" in short) based on the single speaker subset, as described in Section 2.3 and (2) "top_15K" (or "15K" in short) extracted based on top 15,000 videos in terms of average score for each video. Note that top_15K is pruned only based on utterance confidence scores and it may contain multi speaker videos, unlike single speaker. Also a part of these subsets is overlapped.

These subsets are further decomposed into the training and test sets, which will be explained in the next section. We also prepare the various training sets by changing the threshold value θ of the confidence score obtained by CTC segmentation for the single speaker and top_15K subsets. To determine the threshold value, we investigate the distribution of the confidence score over all utterances in the top_15K subset, as shown in Figure 3. This distribution clearly shows that the peak of the distribution starts around -3.0 in both RNN and transformer-based CTC models. Based on the observation, we regard the utterances located in the wide-based region as outlier data points, and use -3.0 as the lowest threshold for pruning in Table 3.

The largest training set is obtained by combining the single speaker and top_15K subsets (train_ss.15k).

Test set design. Focusing on the "single speaker" videos reduces the cost of manual process of verifying audio and transcriptions. The rest of the procedure is as follows: (1) Select 1,621 videos from the "single speaker" videos that include "easy" utterances scored more than -0.3 threshold value based on CTC. (2) Randomly pick up 324 videos, around 20%, and use them as a test video set, which has 3,396 easy utterances in total. (3) Manually listen utterances and identify 1,614 utterances having correct transcriptions. (4) Split them into the development dev_easy Jun21 and evaluation eval_easy Jun21 sets, which have 785 and 829 utterances, respectively. We also made an additional test set with "normal" utterance scored more than -1.0 threshold value. We fixed to use the same test video set as we defined before, and performed steps 3 and 4. We made dev_normal Jun21 and eval_normal Jun21 sets, which have 1,036 and 834 utterances, respectively.

Experimental results. We used an ESPnet state-of-the-art conformer model [5], [24] based on hybrid CTC/attention architectures [33]. The detailed configuration can be found in the ESPnet JTubeSpeech recipe.

Fig. 3. Histograms of the score for different utterances of top_15k.

Table 3. Training and test data statistics for the ASR task. θ is a threshold used to prune bad utterances based on the CTC score.

| Test set          | θ | # videos | # utts | hours |
|-------------------|---|----------|--------|-------|
| dev_easy Jun21    | -0.5 | 110     | 785    | 0.7   |
| eval_easy Jun21   | -0.3 | 106     | 829    | 0.7   |
| dev_normal Jun21  | -1.0 | 128     | 1,036  | 1.1   |
| eval_normal Jun21 | -1.0 | 129     | 834    | 0.8   |
| train_single speaker | -0.5 | 1,297    | 14,797 | 12.7   |
| train_single speaker | -0.5 | 1,297    | 14,797 | 12.7   |
| train_single speaker | -1.0 | 1,297    | 14,797 | 12.7   |
| train_single speaker | -3.0 | 4,342    | 285,846 | 362.0 |
| train_top_15k     | -3.0 | 14,418   | 1,048,699 | 1087.1 |
| train_ss.15k      | -3.0 | 17,761   | 1,270,124 | 1376.9 |

The definition of "easy" and "normal" test sets are determined based on the CTC score objectively. Our listening process and later ASR experiments confirmed that this categorization is reasonable.
Figure 4 shows the ASR performance for various amounts of training data by changing the score threshold $\theta$. We confirmed that the normal test set was more difficult than the easy test set. This result validates our design of the test set by controlling the difficulties based on the score. As regards the amounts of training data, if we increase the amount of training data by reducing $\theta$, the training data may contain more noisy transcriptions or distorted audio segments. Nevertheless, the ASR performance was improved, and the final CERs were 5.2% in eval_easy_jun21 and 10.7% in eval_normal_jun21. These CER ranges are similar to other Japanese ASR benchmarks, e.g., 4 – 6% in CSJ [15] and 13% in LaboroTVspeech [29]. We also list the largest training data case (ss_15k_1376h) by combining the single-speaker subset and top.15k subsets. The performance was improved in most cases except for dev_easy_jun21. This result confirms that more training data is generally helpful to improve the performance of more challenging data.

Finally, we evaluate the effectiveness of CTC segmentation, as discussed in Section 3.2.2. We used train_single speaker with −1.0 score threshold (71.9 hours) and prepared the corresponding training data based on the original YouTube timings only with CTC scoring. Table 4 shows that the CTC segmentation significantly improved the performance and shows the effectiveness of the re-aligning for the YouTube audio data, as suggested by [19].

### Table 4. The effectiveness of CTC segmentation.

|                     | dev_easy | dev_normal | dev_easy | dev_normal |
|---------------------|----------|------------|----------|------------|
| original timing     | 11.5     | 16.5       | 9.2      | 15.7       |
| CTC segmentation    | 9.2      | 14.3       | 6.9      | 13.6       |

3.3. Evaluation in speaker verification

3.3.1. Data cleansing

We used py-webrtcvad [https://github.com/wiseman/py-webrtcvad](https://github.com/wiseman/py-webrtcvad) for VAD and a pre-trained model [https://github.com/yistLin/dvector](https://github.com/yistLin/dvector) for extracting d-vectors. The variation in speaker space was computed from more than 10 utterances for each video. As a pilot study, we used randomly selected 35,000 videos (approx. 30% of total). Figure 5 shows two levels of rapid increase: near 0 and near 8 to 9 on the x-axis. Following the concept in Figure 2, we set a threshold around these levels and assign “TTS,” “single speaker,” or “multi speakers,” class to the videos.

We quantitatively evaluate the authenticity of this classification. We randomly extracted 100 videos from each class and annotated a true class label. Multi-TTS videos and overdubbed-voice videos were annotated as “multi speakers.” To accurately find TTS videos, a TTS specialist participated in this annotation. Table 5 shows that each class has its suitable videos. Especially, the “single speaker” class does not contain multi-speaker videos. Therefore, our method works for choosing the single-speaker videos. Some single-speaker videos leak to the “TTS” class, but this impact is limited because the “TTS” class has only a few videos.

3.3.2. ASV dataset design and models

From the single-speaker videos, 92 unique speakers were selected as the enrollment and testing speakers. For the training and development datasets, 1,795 unique speakers were selected. In the training, 127,997 and 25,392 utterances were used for training and development datasets, respectively. In the testing, we designed an enrollment utterance and a testing one were picked up from the same video but different segments. In the testing, we performed 25,392 trials pairs, included 276 correct pairs and 25,116 incorrect pairs.

We used a speaker embedding network, which was built with four convolutional neural networks, pooling layers and two fully connected layers. As the input feature, 40-order Mel-Frequency Cepstrum Coefficients with 25-ms frame length and half overlapped shift were used. The speaker-embedding vector was 512 dimensions. The evaluation metric is equal error rate (EER) was used for our evaluation by comparing the cosine distance.

3.3.3. ASV performance

We performed ASV evaluations, and the EER of our ASV system with JTubeSpeech was 10.9%. Our system was regarded as the speaker embedding system based on the CNN-based model. Even though such a simple system, this result had the similar performance to the CNN-based model (VGG-M) trained with Voxceleb1 [15]. As a pilot study, we designed a simple benchmark. For example, the result was obtained with the small model and probabilistic linear discriminant analysis (PLDA) scoring and data augmentation techniques were not performed. However, from this simple benchmark, we could show the techniques of data cleaning for selecting a unique speakers and constructing ASV systems performed well. Consequently, we established the Japanese ASV systems with large-scale open source media in the first time.

4. CONCLUSION

In this paper, we propose a speech corpus construction strategy and build 1,300 and 900 hours data for Japanese ASR and ASV. One of our future directions is to extend the corpus to multiple languages.
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