

ESSumm: Extractive Speech Summarization from Untranscribed Meeting

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Abstract

In this paper, we propose a novel architecture for direct extractive speech-to-speech summarization, ESSumm, which is an unsupervised model without dependence on intermediate transcribed text. Different from previous methods with text presentation, we aim at generating a summary directly from speech without transcription. First, a set of smaller speech segments is extracted based on speech signal’s acoustic features. For each candidate speech segment, a distance-based summarization confidence score is designed for latent speech representation measure. Specifically, we leverage the off-the-shelf self-supervised convolutional neural network to extract the deep speech features from raw audio. Our approach automatically predicts the optimal sequence of speech segments that capture the key information with a target summary length. Extensive results on two well-known meeting datasets (AMI and ICSI corpora) show the effectiveness of our direct speech-based method to improve the summarization quality with untranscribed data. We also observe that our unsupervised speech-based method even performs on par with recent transcript-based summarization approaches, where extra speech recognition is required.

Index Terms: automatic speech summarization, extractive summarization, unsupervised, latent semantic analysis, Seq2Seq model

1. Introduction

Speech is a preferred means for communication among humans[1]. Automatic speech summarization is a nontrivial and open task in the research of speech understanding. It has wide real-world applications, including broadcast news summarization [2], podcast summarization [3], clinical conversation summarization [4], and automatic meeting summarization [5, 6]. For example, an automatic meeting summary provides us with an abstract to prepare for an upcoming meeting or review the decisions of previous group [5]. Given a raw human speech as input, speech summarization is the task of generating a summary presented by speech or text to capture the gist and highlights, without losing significant information.

Our proposed method is aimed at directly generating extractive summary from the original speech in an unsupervised manner, especially on untranscribed meetings. While current literature focus on generating a summary based on transcription, developing an efficient method directly from speech that takes advantage of deep speech features has yet to be explored. Specifically, it is motivated and inspired in three aspects. First, our model is a direct speech summarization method. Most automatic speech summarization frameworks utilize text summarization techniques on top of automatic speech recognition (ASR) output, thus they heavily rely on the availability and quality of ASR engines. Because ASR might not function well for the multiparty spoken dialogue or when applied to languages with limited training resources [7, 8], our approach alleviates the problem by directly processing speech signals instead of transcribed text. In this way, our method is applicable to open-domain spontaneous conversations and robust to the possible ASR errors. In addition, ASR systems involve different languages’ annotation data when applied to different languages, so it is not as general as acoustic characteristics in the real world. Second, our model is an extractive-based method. Summarization techniques are typically classified into two categories, extractive [3, 9, 10], and abstractive [11, 12]. While abstractive summarization can be more concise and flexible, however, extractive summarization can preserve the original format and usually be more fluent [13]. In addition, the summarized speech from the original utterance is more understandable than the direct transcribed data of speech [14]. Because of this, our framework is able to naturally and dynamically manipulate the length of generated speech summary, i.e., there is a recent challenge [15] where one-minute duration is selected from the Spotify podcast to give the user a sense of what the podcast sounds like. Most importantly, our method helps when the desired summary results are presented by speech instead of text. This opens the door for the applications including the live stream broadcasting [16]. Last, our approach is fully unsupervised. Compared with the supervised method [10], no additional annotation data is needed to build the speech summarization model.

To this end, we design a simple yet efficient speech-to-speech summarization framework, ESSumm, which is aimed at automatically and efficiently summarizing the raw speech input without transcribed data. Our main contributions are three-fold,

- To the best of our knowledge, ESSumm is the first architecture to explore and incorporate deep speech features with latent semantic analysis to the task of meeting speech summarization.
- ESSumm is an adaptively extractive speech-to-speech meeting summarization framework in a fully unsupervised manner.
- ESSumm could easily concatenate the extracted key speech segments together and produce the short audio summary without additional ASR and speech synthesizer steps.

2. Related work

2.1. Acoustic-based speech summarization

Direct speech summarization approaches have been underexplored in literature. There have been a limited number of prior works that directly deal with speech inputs for automatic speech summarization without transcription [7, 17, 18, 19, 20]. Maskey et al. [17] examine Hidden Markov Model on acoustic and prosodic features to select segments for spoken documents, while Flamary et al. [7] search for the repeated recurrent speech patterns. [19] summarizes multiple spoken documents by identifying recurring acoustic-based patterns. [18] applies
the computer vision techniques to detect possible repetition. Recently, [20] investigates the turn-taking features to examine whether meeting segments contain extractive summary dialogue acts. However, those previous works mainly focus on identifying the recurrent patterns or using the handcrafted features. Instead, our approach summarizes meetings in a distance-based manner from extracted deep speech features.

### 2.2. Transcript-based speech summarization

Existing works [21, 11, 12, 10, 22, 9, 23] commonly formulate the speech summarization problem to be a text summarization problem in a two-stage process, due to the fact that there have been considerable works and rapid progress in the task of text summarization [24, 25, 26]. Specifically, they first use ASR engines to generate transcripts from the audio input, which is the word-level information, and then apply the existing mature text summarization methods to produce the summary. Among those transcript-based models, the pioneer maximum marginal relevance (MMR) [21] iteratively selects the most relevant sentence that is similar to the whole document. TextRank [11] is a graph-based keywords extraction algorithm where each keyword is represented by a node in the graph. ClusterRank [12] extends TextRank [11] by including measures for noise and redundancy. HMNet [10] implements an encoder-decoder transformer-based network. [22] designs an objective function that is optimized by the greedy algorithm for the extractive summarization in the meeting domain. [9] employs a graph-based method for text-based abstractive summarization in an unsupervised manner. [23] extends to model the concept from various modalities. The focus of all above transcribe-and-summarize work, however, is primarily limited to conduct on error-prone transcripts. In this work, we are aimed at achieving summarization in a speech-to-speech manner without transcription.

### 2.3. Representation learning on speech

Recently, there are several works focusing on utilizing the pre-trained speech representations on different speech-related tasks, including speech recognition [27, 28] and speech enhancement [29]. Compared with the traditional handcrafted features, including pause, duration, fundamental frequency (F0), and Mel Frequency Cepstral Coefficients (MFCCs), a variety of pre-trained representations obtain significant improvements in the task of speech recognition [27]. Specifically, the recent Wav2Vec2.0 [28] is a transformer-based speech framework that is trained by predicting speech units for masked parts of the audio. Built on the deep speech representations from Wav2Vec2.0 [28], our summarization framework captures rich relationships among speech segments and produces an effective summary.

### 3. Our approach

In this work, we focus on the task of extractive summarization. ESSumm takes raw speech as input and generates a summary that covers the most important information. Our goal is to perform speech summarization and generate an extractive summary without transcribed text, where we are able to preserve attributes such as the speaker’s voice, presentation style, type of humor, and production quality. There are mainly two challenges in our task. First, all important key segments should be covered and included in the output summary. Second, the generated summary should be sequential and organized.

As illustrated in Figure 1, there are three main steps in the proposed architecture, including segments generation, key-segments extraction, and key-segments concatenation. To deal with the first challenge, ESSumm builds on the recent work to extract deep speech feature representations. Specifically, we extract the deep speech feature representations using the pre-trained Wav2Vec2.0 [28], and then project them into high dimensional phoneme probability with k-means clustering algorithm, and score and rank the importance of segments based on Euclidean distance using latent semantic analysis. To solve the second challenge, we concatenate the key segments together to form the output speech summary with the length constraint.

#### 3.1. Segments generation

Speech audio is a continuous signal that captures many aspects of the recording with no clear segmentation into words or other units [28]. Given the raw input speech, most existing summarization works tend to generate the speech segments based on the ASR transcripts, essentially doing text preprocessing to get sentence-level segmentation [3, 10, 9, 23]. Alternatively, we divide the whole input speech into a number of smaller segments based on the acoustic information of silence regions following [20], where they use ‘spurt’ that separates input speech by at least 500ms silence. In this way, we extract the segments based on the speech silence gap and don’t rely on the availability and quality of ASR engines, which commonly is not optimal under
the adverse acoustic circumstances [8].

3.2. Key-segments extraction
On top of individual speech segments from the first stage, we perform segment scoring and segment selection. Naively, we are able to detect the key segments based on turn-taking information, for example, the absolute difference of average pitch for each speech segment [20]. Alternatively, we propose to leverage pre-trained Wav2Vec2.0 [28] to extract the deep speech-related features for speech segment. Then we use latent semantic analysis based on the metric distance of speech representation to score and rank the importance of candidate segments.

Motivated by the observation [28] that Wav2Vec2.0 facilitates learning of high-level contextualized representations and has shown its potential in improving the task of speech recognition, we employ the pre-trained Wav2Vec2.0 [28] to extract the deep speech features for each segment. Each speech segment is encoded by the deep speech-related feature representation instead of the hand-crafted acoustic features. In our case of speech summarization, the pre-trained Wav2Vec2.0 model enables us to encode the powerful latent speech representation.

On the other hand, we leverage latent semantic analysis in this work. First, the speech representation is projected to a high-dimensional phoneme probability. Heuristically, we apply k-means clustering on the extracted deep speech feature representation to get a sequence of phoneme cluster IDs for each segment. In this way, we use the vector speech model representation to represent each segment with a sequence of cluster IDs. As illustrated in the K-means clustering module in Figure 1, different circles for each speech segment refer to its projected vectors. Specifically, different colors correspond to different cluster IDs. Next, we represent each speech segment based on the term frequency–inverse document frequency (TF-IDF) of phonemes. Inverse document frequency (IDF) [30] is a widely used lexical statistical feature in classic information retrieval models. In our case, the TF-IDF vectors are able to capture the phonemes significance. In detail, we adopt the TF-IDF value to measure redundancy and relevance for each speech segment, with the term frequency (TF) being calculated on the segment level and the inverse document frequency (IDF) calculated on the whole input speech. After we get the vector representation for each segment based on TF-IDF, we exploit the principal component analysis (PCA) to represent the whole input speech and we employ the Euclidean distance to the eigenvectors of the whole audio input as the confidence score. Specifically, the Euclidean distance between TF-IDF vectors of each segment and eigenvectors of the whole speech input is inversely proportional to the confidence scores.

As the key part of ESSumm, the Wav2Vec2.0 deep speech feature extraction module supports efficient and effective speech feature modeling. Because Wav2Vec2.0 learns the speech units common to several languages, our framework benefits from it and is general to multiple different languages. In addition, compared with other supervised meeting summarization approaches, expensive and time-consuming annotations are not required. To this end, we believe that Wav2Vec2.0-based features combined with latent semantic analysis facilitate and directly predict the relative importance of speech segments.

3.3. Key-segments concatenation
Last, we extract the highest-scoring segments to form an extractive summary of the raw input speech audio. We specify the length of the generated summary by a predefined summary time length or by a predefined word count, where we simply generate all the importance-based order of speech segments, and then calculate the length until the target summary length is reached. Most previous works generate the target summary based on the word count. However, the recent challenge [15] is aimed at producing one-minute summary from the original podcast. In our case, since the target length is preferred in terms of time length over word number, so ESSumm naturally meets the requirement without an additional speech synthesizer step.

To this end, the quality of generated speech summary can be improved in two aspects. First, the state-of-the-art self-supervised neural network Wav2Vec2.0 [28] accurately captures the speech unit features from raw input audio and learns powerful speech representation from speech segments. To the best of our knowledge, ESSumm is the first work to directly employ a self-supervised neural network on speech summarization task. Second, ESSumm could easily concatenate the extracted key speech segments together and produce a short audio summary without additional ASR and speech synthesizer steps.

4. Experiments
In this section, we evaluate our proposed method on the AMI corpus [31] and ICSI meeting corpus [32]. There has been a shortage of annotated datasets that are tailored for the speech-to-speech summarization task. We begin by giving a brief overview of the datasets in Table 1. Then, we validate the effectiveness of our proposed method by comparing it with the existing approaches on the widely used ROGUE score metric.

Table 1: Statistics of meeting summarization datasets

| Datasets | AMI | ICSI |
|----------|-----|------|
| # Meetings | 137 | 59 |
| # Speakers | 4.0 | 6.3 |
| # Turns | 535.6 | 819.0 |
| # Len. of Meet. | 6007.7 | 13317.3 |
| # Len. of Sum. | 296.6 | 488.5 |

4.1. Dataset

AMI meeting corpus The AMI corpus [31] is a multi-modal dataset consisting of 100 hours of meeting recordings which is widely used in recent research on meeting summarization. As demonstrated in Table 1, there are 137 meetings in total, each of which involves 4 speakers who work on designing a remote control given variable information. We adopt the traditional test set of 20 meetings following [33, 6, 9]. The average length of summary is 296.6 tokens. There is one abstractive summary for each meeting in the test set. The speech recognition transcripts provided in the dataset show a word error rate (WER) of 36%.

ICSI meeting corpus The ICSI meeting corpus [32] is an audio dataset consisting of 70 hours of meeting recordings. As shown in Table 1, there are 39 meetings in total, each of which involves 6.3 speakers. Different from AMI, the contents of ICSI meetings are specific to the discussions about research among students. We adopt the traditional test set of 6 meetings following [9, 6]. There are three abstractive summaries for each meeting in the test set. The speech recognition transcripts provided within the dataset show a WER of 37%.

4.2. Implementation details
For the segments generation stage, we instead use the provided corpus’s dialogue act scripts to once to align with the existing
methods. Here, we only use the sentence-level information, including the sentence speech segments and their corresponding start-end time in the input audio. Note that we could use the acoustic information to extract segments as well, however, in this case, we are unable to make a fair comparison with existing approaches. Similar to [9], we randomly select 15 meetings as a development set from the training set for each corpus in order to perform parameter tuning.

Table 2: \textit{ESSumm} outperforms existing acoustic-based speech summarization methods for ROUGE on AMI corpus test set compared with abstractive ground truth summary using ASR transcriptions. We are using macro-averaged results for 350 word summaries

| Method         | AMI ROUGE-1 (%) | AMI ROUGE-2 | AMI ROUGE-SU4 | ICSI ROUGE-1 (%) |
|----------------|-----------------|-------------|---------------|------------------|
| Murray et al. [3] | 0.041           | 0.009       |               |                  |
| ESSumm         | 0.088           | 0.120       |               |                  |

Specifically, we set the number of phonemes to be 32. We project the deep speech features representations obtained from Wav2Vec2.0 [28] to 32 channels. Heuristically, we use four principal components in terms of PCA for AMI and two principal components for ICSI when we calculate the Euclidean distance. Although ESSumm is preferred with speech summary constrained by a target time length, however, it is flexibly adapted to a predefined word count as long as the corresponding timestamp information is provided. In terms of the target summary length, we follow [22, 6] with different word counts for AMI and ICSI, respectively.

4.3. Evaluation metrics

To be consistent with previous works [5, 21, 22, 9], we adopt the widely used text summarization evaluation metrics: calculating Recall Oriented Understudy for Gisting Evaluation\textit{(ROUGE)} [34, 35]. ROUGE is a score of overlapping between the generated summary and the ground truth summary, i.e., ROUGE-1 measures the overlapping of unigrams, and ROUGE-2 refers to the overlapping of bigrams. We utilize the human abstracts as the reference summaries and employ ROUGE-2.0 package [35] to evaluate our models. We report the recall, precision and F-1 measure scores for the summarization system performance.

Table 3: \textit{ESSumm} outperforms existing sentence-level transcript-based speech summarization methods for all ROUGE levels F-1 measure scores on AMI and ICSI corpora test sets compared with abstractive ground truth summary using ASR transcriptions. Following [6], we are using macro-averaged results for 300 and 500 word summaries

| Method         | AMI ROUGE-1 (%) | AMI ROUGE-2 | AMI ROUGE-SU4 | ICSI ROUGE-1 (%) |
|----------------|-----------------|-------------|---------------|------------------|
| MMR [21]       | 0.24            | 0.04        | 0.00          |                  |
| Concepts [6]   | 0.30            | 0.05        | 0.08          |                  |
| ESSumm         | 0.35            | 0.06        | 0.12          |                  |

4.4. Experimental results

Different experimental setups and evaluation criteria, including generated summary type, generated summary length, and reference type, make it challenging to compare previous works [33]. Towards it, we manually divide the existing methods into three categories, acoustic-based, sentence-level transcript-based, and word-level transcript-based extractive summarization. Among the latter two, it is nontrivial for the word-level method to produce the summarized speech from the original utterance, while it is practical for the sentence-level approaches as long as the sentence-timestamp pair information is provided.

As demonstrated in Table 2, \textit{ESSumm} outperforms the existing acoustic-based extractive summarization method for both ROUGE-2 and ROUGE-SU4 levels on the AMI corpus test set compared with abstractive ground truth summary using ASR transcriptions. Our results demonstrate that by leveraging state-of-the-art transformer-based acoustic model and latent semantic analysis techniques, a realistic speech summary can be generated to enhance the summarization quality without transcribed data in the real world. Shown in Table 3, \textit{ESSumm} outperforms existing sentence-level transcript-based extractive summarization methods for all ROUGE levels on AMI and ICSI corpora test sets compared with ground truth abstractive summary using ASR transcriptions. We are using macro-averaged results for 300 and 500-word summaries following [6], respectively.

In addition, we compare our framework with the existing word-level transcript-based summarization methods on both AMI and ICSI datasets. Traditional extractive summarization methods based on selecting and reordering salient words tend to produce summaries that are not natural and incoherent [37]. As can be seen from Table 4, despite its simplicity, our approach works comparably well with previous extractive summarization methods on both AMI and ICSI datasets. Note that although our results are partially constrained by the audio segments specified by the corpus’s dialogue act scripts, our method is competitive with the salient word-level methods.

5. Conclusions

In this work, we present a simple yet efficient framework for extractive speech-to-speech summarization, which employs latent speech representation in an unsupervised manner that reduces the requirement of manual annotations. Unlike the existing work, we can directly generate the summarized speech without the extra speech synthesizer step. Without bells and whistles, experimental results show that the proposed speech-based method is effective for the task of extractive speech summarization in the AMI and ICSI corpora.

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7. References

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