

1. Introduction

Task

Determining speaker change time boundaries in recorded speech Motivation

- Speaker Change Detection (SCD) benefits speaker diarization, speaker tracking and transcribing audio with multiple speakers
- Current state-of-the-art SCD system may still improve
- Speaker information in training data and content information in dialog have not been fully utilized

Goal

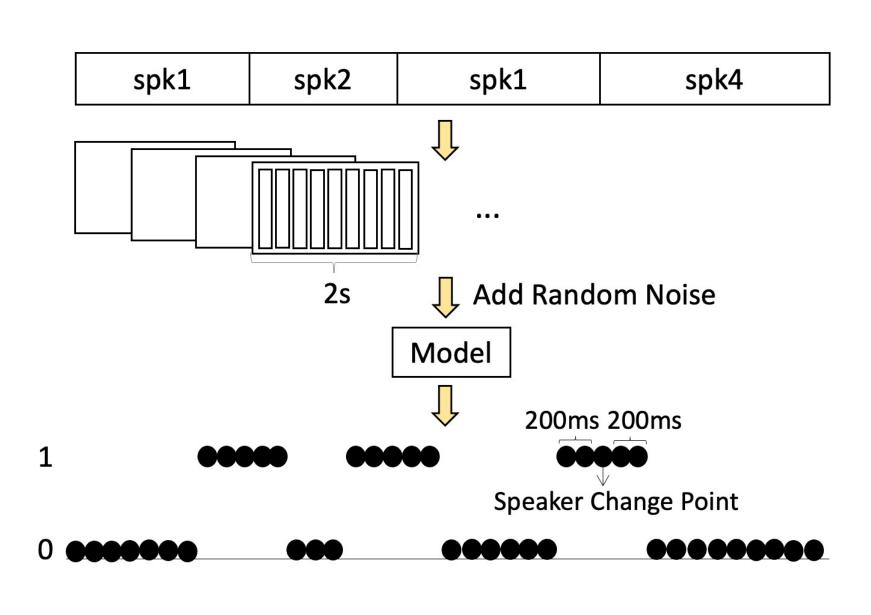
- Improve the state-of-the-art SCD system in terms of :
- Utilize speaker information in training data
- Add content information extracted from discussion dialog audio

2. Baseline System

Baseline System (see Figure 1): MFCC Recurrent or layers ·IIIIIII III II SinConv Figure 1: Model architecture of the baseline system

Training

- Figure 2 shows training process
- Splitting audio sequence
- Add random noise
- Feed into model
- Predict 1/0 (change/not change)
- Cross Entropy loss



Prediction

- Figure 3 shows the prediction process
 - Splitting audio sequence
 - Feed into the trained model

 - Take the average
 - Decide the boundary

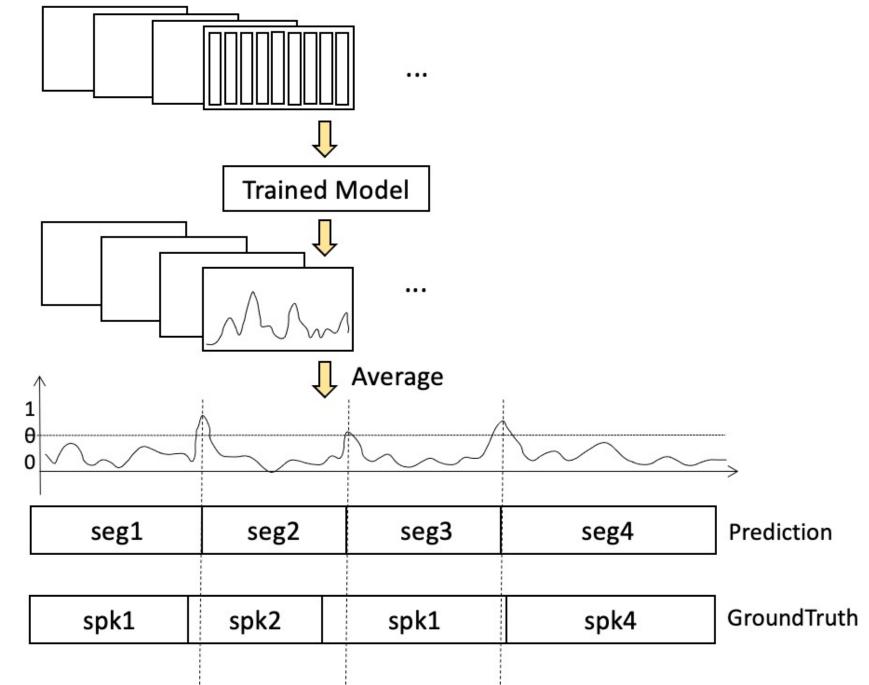


Figure 2: Training process for speaker change detection

A Multitask Learning Framework for Speaker Change Detection with Content Information from Unsupervised Speech Decomposition ¹Hang Su, ¹Danyang Zhao, ¹Long Dang, ²Minglei Li, ¹Xixin Wu, ¹Xunying Liu, ¹Helen Meng

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- Predict 1/0 (change/not change)

Proposed Approach (see Figure 4)

Multitask Learning

- Goal: Utilize speaker information
- Add a "Speaker Branch"
- Predict speaker (Cross Entropy loss)
- Distinguish speakers (Triplet loss)

Unsupervised Speech Decomposition

- Goal: Add content information
- Pretrain a decomposition model
- Decompose spoken information into pitch, rhythm, timbre and content
- Encoder \rightarrow Decoder with MSE loss

Training and Prediction

- Splitting audio sequence

Dataset – AMI corpus

- Collection of conversational recordings in meeting domain
- 4~5 speakers in each conversation

Evaluation Metric

• Coverage : r: reference segment; h: hypothesis segment

coverage(R, H) =

- F1 : harmonic average of coverage and purity

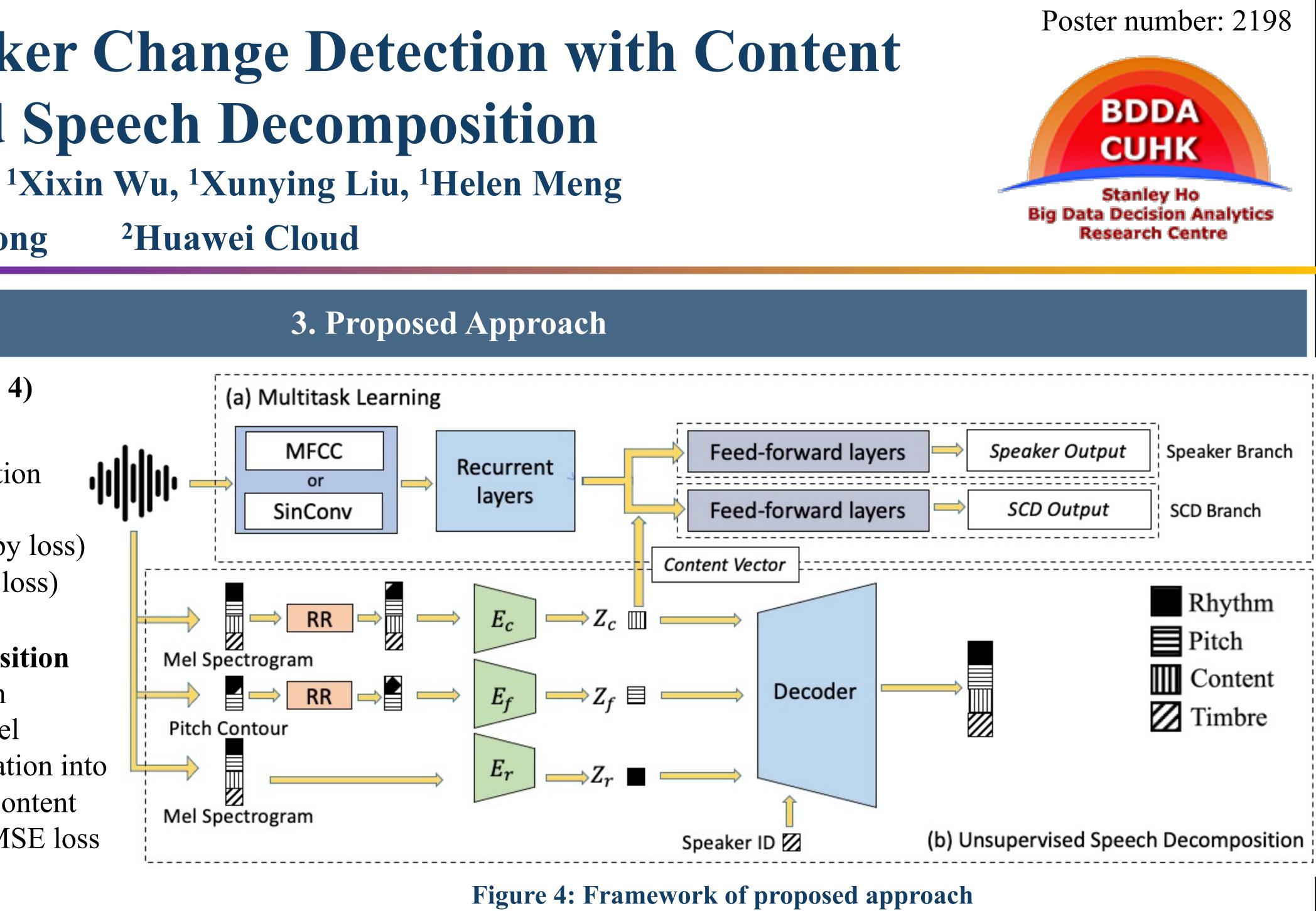
Results

- Table 1 shows the results of using MFCC as the input
- Table 2 shows the results of using waveform as the input

| Validation | | | Test | | |
|------------|--|--|--|--|--|
| Purity | Coverage | F1 | Purity | Coverage | F1 |
| 85.01 | 79.90 | 82.27 | 86.54 | 80.72 | 83.53 |
| 85.08 | 80.78 | 82.87 | 87.04 | 81.18 | 84.01 |
| 85.07 | 79.98 | 82.44 | 86.84 | 82.97 | 84.34 |
| 85.02 | 81.14 | 83.03 | 86.04 | 83.31 | 84.65 |
| 85.04 | 81.68 | 83.33 | 86.16 | 84.56 | 85.35 |
| | Purity 85.01 85.08 85.07 85.02 | PurityCoverage85.0179.9085.0880.7885.0779.9885.0281.14 | PurityCoverageF185.0179.9082.2785.0880.7882.8785.0779.9882.4485.0281.1483.03 | PurityCoverageF1Purity85.0179.9082.2786.5485.0880.7882.8787.0485.0779.9882.4486.8485.0281.1483.0386.04 | PurityCoverageF1PurityCoverage85.0179.9082.2786.5480.7285.0880.7882.8787.0481.1885.0779.9882.4486.8482.9785.0281.1483.0386.0483.31 |

Figure 3: Prediction process for speaker change detection

Table 1: Results of using MFCC as the input



Feed into both Multitask Learning model and pre-trained Unsupervised Speech Decomposition (USD) model Obtain content vector from USD model, then feed into Multitask Learning model Predict 1/0 (change/not change) in Multitask Learning model

4. Experiments

70 hours for training, 15 hours for validation, 15 hours for test

$$\frac{\sum_{r \in R} \max_{h \in H} |r \cap h|}{\sum_{r \in R} |r|}$$

• Purity : dual metric of coverage where role of h and r interchanged

| Validation | | | Test | | | |
|------------|--|--|--|--|--|--|
| Purity | Coverage | F1 | Purity | Coverage | F1 | |
| 85.38 | 89.49 | 87.39 | 85.62 | 89.71 | 87.62 | |
| 85.00 | 90.51 | 87.67 | 85.16 | 90.92 | 87.95 | |
| 85.00 | 91.74 | 88.24 | 85.61 | 91.04 | 88.24 | |
| 85.26 | 91.49 | 88.27 | 85.66 | 91.02 | 88.26 | |
| 85.00 | 91.92 | 88.32 | 85.68 | 91.75 | 88.61 | |
| | Purity 85.38 85.00 85.00 85.26 | PurityCoverage85.3889.4985.0090.5185.0091.7485.2691.49 | PurityCoverageF185.3889.4987.3985.0090.5187.6785.0091.7488.2485.2691.4988.27 | PurityCoverageF1Purity85.3889.4987.3985.6285.0090.5187.6785.1685.0091.7488.2485.6185.2691.4988.2785.66 | PurityCoverageF1PurityCoverage85.3889.4987.3985.6289.7185.0090.5187.6785.1690.9285.0091.7488.2485.6191.0485.2691.4988.2785.6691.02 | |

- the AMI dataset for SCD task

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Table 2: Results of using waveform as the input

5. Conclusions

Utilize speaker information with proposed multitask learning architecture to improve performance of SCD Add spoken content vectors extracted from pre-trained

unsupervised speech decomposition model to further improve performance of SCD task

Proposed approach achieved new state-of-the-art result on

6. Acknowledgements