Aligning Audiovisual Features for Audiovisual Speech Recognition

Fei Tao and Carlos Busso

Multimodal Signal Processing (MSP) Laboratory
Department of Electrical Engineering,
The University of Texas at Dallas,
Richardson TX-75080, USA
Audiovisual approach for robust ASR

DNN emerges for AV-ASR

- Neti et al. [2000] GMM-HMM
- Ngiam et al. [2011] Multimodal deep learning
- Petridis et al. [2018] End-to-end AV-ASR
Introduction

- Fusing audiovisual features followed static fashion
  - Linear interpolation (extrapolation) to align
- Audiovisual modalities fusion on decision, model or feature levels.

How to align audiovisual modalities?
Motivation

- Phase between lip motion and speech [Tao et al., 2016]

- Bregler and Konig [1994] show the best alignment was with a shift of 120 milliseconds
  - However, phase is time variant so this may not be the optimum approach
Motivation

- Audiovisual features concatenated frame-by-frame:
  - For some phonemes, lip movements precede speech production
  - For other phonemes, speech production precede lip movements

- In some cases, audiovisual modalities are well aligned [Hazen, 2006]
  - Pronounce the burst release of /b/

- Co-articulation effects and articulator inertia may cause phase difference
  - Lip movement can precedes audio for phoneme /m/ in transition /g/ to /m/ (e.g., word segment)
Deep Learning for Audiovisual

- **Deep learning for audiovisual ASR:**
  - Ninomiya et al. (2015) extracted bottleneck feature for audiovisual fusion
  - Ngiam et al. (2011) proposed bimodal DNN for fusing audiovisual modalities
  - Tao et al. (2017) extended to bimodal RNN on AV-SAD problem for modeling audiovisual temporal information

- **Rely on linear interpolation to align audiovisual features**

**Proposed Approach:**
Learn alignment automatically from data using attention model
Outline

1. Introduction
2. Proposed Approach
3. Corpus Description
4. Experiment and Result
5. Conclusion
Proposed Framework

- Proposed approach relies on attention model
- Attention model learns alignment in sequence-to-sequence learning
  - Output is represented as linear combination of input at all time points
  - Learn the weights in linear combination following a data-driven framework

\[ c_i = \sum_{j=1}^{T} a_{ij} h_j \]
Alignment Neural Network (AliNN)

Feature space transform
Temporal alignment
Alignment Neural Network (AliNN)

Feature space transform

Static Part

Temporal alignment

Dynamic Part

Feature Extractor

Attention Model
Alignment Neural Network (AliNN)

Temporal align
Dynamic Part
Alignment Neural Network (AliNN)

Feature space transform
Static Part

Temporal align
Dynamic Part
Alignment Neural Network (AliNN)
Alignment Neural Network (AliNN)
Training AliNN

- Training AliNN on the whole utterance is computationally expensive
- We segment the utterance into small sections
  - Length of each segment is 1 sec, shifted by 0.5 sec
  - Sequence is padded with zeros if needed

![Zero padding diagram]
CRSS-4ENGLISH-14 corpus:

- 55 females and 50 males (60 hrs and 48 mins)
- Ideal condition: high definition camera and close-talk microphone
- Challenge condition: tablet camera and tablet microphone
- Clean section (read and spontaneous speech) and noisy section (subset of read speech)
Audiovisual Features

- Audio feature: 13D MFCCs feature (100 fps)
- Visual feature: 25D DCT + 5D geometric distance
  - 30 fps for high definition camera
  - 24 fps for tablet camera
Experiment Setting

- 70 speaker for training, 10 for validation, 25 for testing
  - Gender balanced
  - Train with ideal condition under clean environment
  - Test with different conditions under different environments

- Two backend:
  - GMM-HMM: augmented with delta and delta-delta information
  - DNN-HMM: 15 context frames

- Data of tablet (24 fps) is linearly interpolated to 30 fps
- Linear interpolation for pre-processing as baseline
- Focus on word error rate (WER)
Experiment Results

- Under ideal condition, the proposed front-end always achieves the best performance.

- Under tablet condition, the proposed front-end achieve the best performance except GMM-HMM backend.
  - Linear interpolate tablet data to 30 fps may impair the advantage of AliNN.

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<thead>
<tr>
<th>Front-end</th>
<th>MODEL</th>
<th>Ideal Conditions</th>
<th>Tablet Conditions</th>
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</thead>
<tbody>
<tr>
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<td>GMM-HMM</td>
<td>23.3</td>
<td>24.2</td>
</tr>
<tr>
<td>AliNN</td>
<td>GMM-HMM</td>
<td><strong>17.5</strong></td>
<td><strong>19.2</strong></td>
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<tr>
<td>LInterp</td>
<td>DNN-HMM</td>
<td>4.2</td>
<td>4.9</td>
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<tr>
<td>AliNN</td>
<td>DNN-HMM</td>
<td><strong>4.1</strong></td>
<td><strong>4.5</strong></td>
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## Results Analysis

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<td></td>
<td></td>
<td>Clean</td>
<td>Noise</td>
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**Note:** The values in **red** indicate the highest noise levels for both conditions.

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### Ideal

![Ideal SNR plot](image)

### Tablet

![Tablet SNR plot](image)
This study proposed the alignment neural network (AliNN)
- Learns the alignment between audio and visual modalities from data
- Does not need alignment or task label

The proposed front-end is evaluated on CRSS-4ENGLISH-14 corpus
- Large corpus for AV-LVASR (over 60h)
- The proposed front-end outperforms simple linear interpolation under various conditions

Future work will extend approach to end-to-end framework
References:


