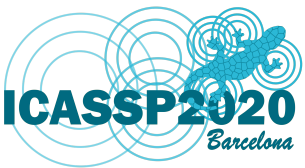
An Analysis Of Speech Enhancement And Recognition Losses In Limited Resource Multi-Talker Single Channel Audio-Visual ASR

Luca Pasa, Giovanni Morrone, Leonardo Badino
ICASSP 2020

ISTITUTO ITALIANO DI TECNOLOGIA

UNIMORE
UNIVERSITÀ DEGLI STUDI DI MODENA E REGGIO EMILIA



ASR and the Cocktail-Party Problem

- State-of-the-art ASR can be very accurate but **performance drops signi cantly in a cocktail party scenario**
- Recognizing the speech of a target speaker mixed with other people speech's in a single-channel audio is an **ill-posed problem**

  Many different hypotheses about what the target speaker says are consistent with the mixture signal, **we do not know which utterance corresponds to the target speaker**

  We addressed this problem by exploiting an additional information: **the video of talking face of the target speaker**

- Some robust ASR systems process the audio signal through a speech enhancement or separation stage
- Jointly training the ASR and enhancement modules can be more beneficial than training them separately
- **Goal: analyze the interaction between the ASR and enhancement tasks**

  Understand whether (and how) it is advantageous to train them jointly
- **How?**

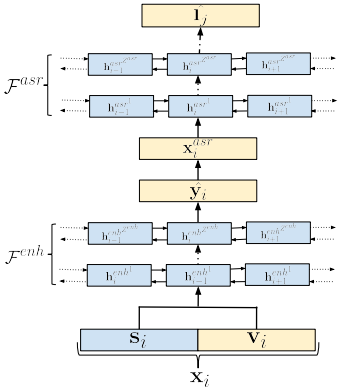
  Train and analyze a simple AV-ASR model

  Analyze whether adding a preliminary speech enhancement stage helps in performing the ASR task

Joint Model

We analyze a simple and common architecture:

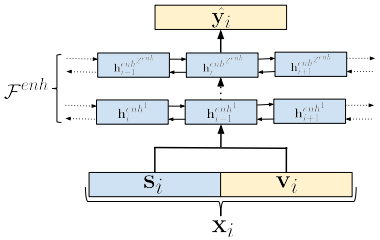
- Based on deep-BLSTM
- Composed of 2 sub-models:
  - Enhancement Model
  - ASR Model
- With the following model inputs:
  - Noisy Audio information: $\mathbf{s} = [\mathbf{s}_1; \dots; \mathbf{s}_T]$
  - Face Motion vector: $\mathbf{v} = [\mathbf{v}_1; \dots; \mathbf{v}_T]$
- Where only the enhancement part exploits the visual information, while the ASR part receives in input only the output of the speech enhancement module



Enhancement Model

- **Goal:** de-noising the speech of the speaker of interest
- **Input** at time step i: $\mathbf{x}_i = \begin{matrix} \mathbf{s}_i \\ \mathbf{v}_i \end{matrix}$;
- **Target:** a slice of the spectrogram of the clean utterance spoken by the target speaker.
- **Loss function:** Mean Squared Error (MSE)

  $L^{enh}(\mathbf{y}_i, \hat{\mathbf{y}}_i) = MSE(\mathbf{y}_i, \hat{\mathbf{y}}_i)$:

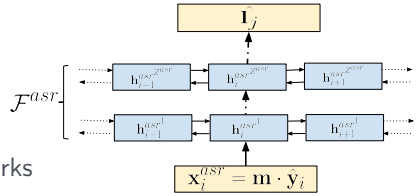


ASR Model

- Input: computes the mel-scale filter bank representation derived from the spectrogram s_i
- Maps $\mathbf{x}_i^{asr}$ to the phone label $\hat{\mathbf{l}}_i$ by using Z^{asr} BLSTM layers
- Uses the CTC loss

$$L^{asr}(\mathbf{l}_j; \hat{\mathbf{l}}_j) = CTC_{loss}(\mathbf{l}_j; \hat{\mathbf{l}}_j)$$

- 3 different versions:
  1. Fed with acoustic features
  $$\mathbf{x}_i^{asr} = \mathbf{s}_i^m$$
  2. Fed with motion vector computed from face landmarks
  $$\mathbf{x}_i^{asr} = \mathbf{v}_i$$
  3. Uses both audio and visual features
  $$\mathbf{x}_i^{asr} = \begin{matrix} \mathbf{s}_i^m \\ \mathbf{v}_i \end{matrix}$$



Two Training Strategies

Goal: Analyse the behaviors of the ASR and enhancement loss

- **Joint training**

  $L_{join} = L^{enh} + L^{asr}$

  We explored 2 different types of :

  - Constant
  - Adaptive: $_{adapt} = 10^{\lfloor \log_{10}(\mathcal{L}^{asr}) \rfloor} = 10^{\lfloor \log_{10}(\mathcal{L}^{enh}) \rfloor}$

- **Alternated training**

  Alternation of speech enhancement and ASR training phases

  Performs a few steps of each phase several times

  Alternated two full phases training

  - the two phases are performed only one time each

  The L^{asr} optimization phase updates both ^{enh} and ^{asr} parameters

  Weight freezing: optimize L^{asr} by only updating ^{asr}

Experimental Setup

- Two Audio-visual limited-size datasets

  GRID, **TCD-TIMIT**

  Speaker-independent

  Respectively split into disjoint sets of 25/4/4 and 51/4/4 speakers for training/validation/testing

  Used standard TIMIT phone dictionary

  - GRID: 33 phones, TCD-TIMIT: 61 phones

- Baseline

  ASR-only models

  - 2 layers of 250 hidden units and were trained by using back-propagation through time (BPTT) with Adam optimizer

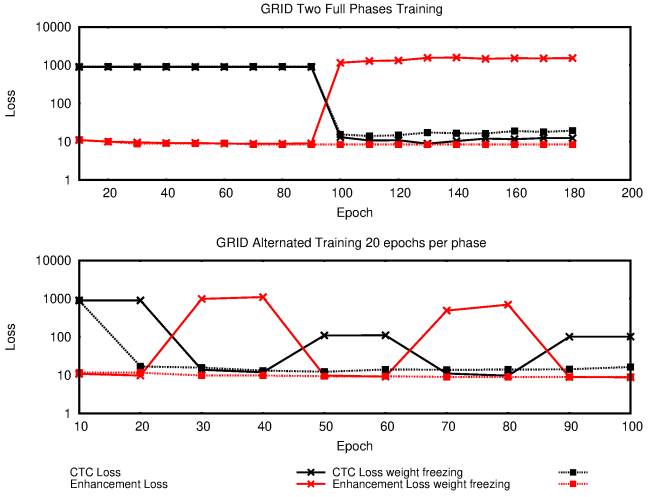
- Joint Model

  Same number of layers for both ASR and enhancement components

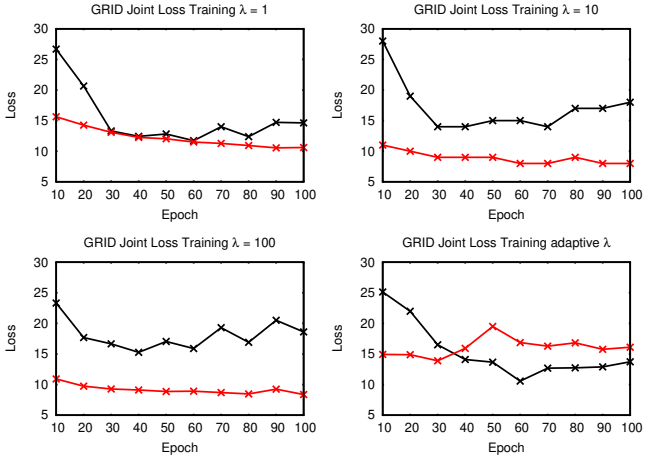
Experimental Results

Training Method	GRID PER	TCD-TIMIT PER-61	TCD-TIMIT PER-39
Baseline-ASR-Mod. Clean-Audio	5:8	46:7	40:6
Baseline-ASR-Mod. Mixed-Audio	49:4	78:4	71:3
Baseline-ASR-Mod. Mixed-A/V	49:9	77:2	70:9
Baseline-ASR-Mod. Visual	29:4	78:6	74:7
Joint-Mod. Joint Training	15:4 = 1	53:1 =	47:7 *adapt*
Joint-Mod. Alt. Training 2 full	16:0	45:6	41:2
Joint-Mod. Alt. Training 2 full freeze	18:7	**44:3**	**40:0**
Joint-Mod. Alt.Training	**13:9**	44:9	40:6
Joint-Mod. Alt. Training freeze	18:1	61:3	55:5
Joint-Mod. PIT Alt. Training	43:3	67:1	62:4

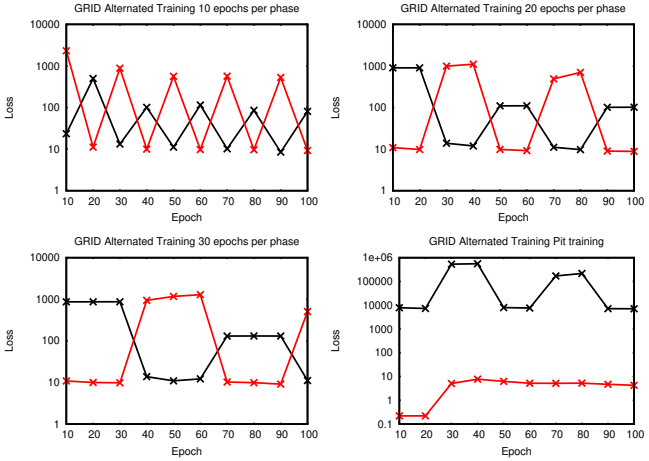
Alternate Training Analysis



Joint Loss Training Analysis



Alternated Training Analysis



Conclusion

- Jointly minimizing the speech enhancement loss and the CTC loss may not the best strategy to improve ASR
- Alternation of the speech enhancement and ASR training phases
  - The loss function that was not considered for the training phase tends to diverge
- The interaction between the two loss functions can be exploited in order to obtain better results
  - The alternated training method shows that the recognition error can be gradually reduced by wisely alternating the two training phases

Thanks for the attention!

Contacts:
Luca Pasa: lpasa@math.unipd.it
Giovanni Morrone: giovanni.morrone@unimore.it
Leonardo Badino: leobad08@gmail.com