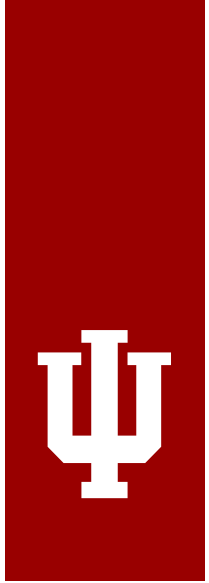

A RETURN TO DEREVERBERATION IN THE FREQUENCY DOMAIN USING A JOINT LEARNING APPROACH

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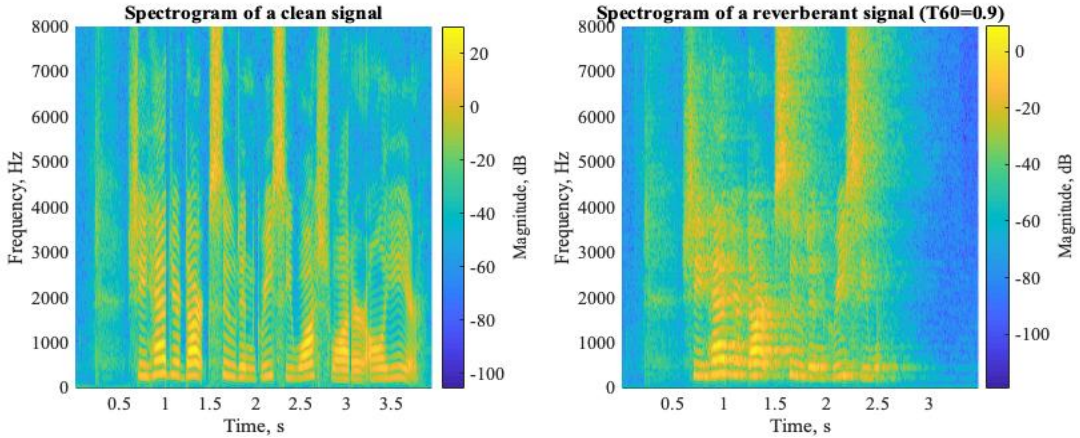
Yuying Li and Donald S. Williamson

LUDDY

SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING

Why Dereverberation?

- Reverberation degrades perceptual speech quality and intelligibility as sound reflections obscure signal structure
- The presence of reverberation may undermine our listening experience
- The reverberation could affect many applications, such as, hearing aids, automatic recognition (ASR) and speaker identification



Previous Studies

- LSTM predicts reflections in time-frequency (T-F) domain. The prediction is subtracted from the reverberant speech signal [5]
  - Pro: LSTM captured time information that could help predicting the late reflections
  - Con: performed on magnitude ignored phase, which could affect the results.

- DNN predicts complex ratio mask (cIRM), where the mask enhances the magnitude and phase [3]
  - Pro: cIRM combined both magnitude and phase information
  - Con: DNN could not capture the continuous time information

- Weighted prediction error (WPE), estimates an inverse filter that is subtracted from the reverberated speech [6, 7]
  - Pro: handles both multi-channel and single-channel situation, more generalization
  - Con: did not perform as well as DNN approaches

- Another approach that uses T-F domain features to predict a dereverberation mask (DM) and IRM [8]
  - Pro: can do source separation and dereverberation at the same time
  - Con: lack of time information

Frequency vs. T-F domain

- Dereverberation is often performed in the time-frequency domain using mostly deep learning approaches
- Time-frequency domain processing, however, may not be necessary when reverberation is modeled by the convolution operation
- Many previous studies performed in the frequency-domain (e.g. independent component analysis (ICA)) [12]
  - They require assumptions to hold in different environments, which is not often the case.
  - A frequency-domain deep learning-based approach, however, may not need to make these assumptions

Problem formulation

- **Objective**: remove the late reflections from the corresponding reverberant speech signal by operating in the frequency domain

- **Prediction target**: direct plus early RIR in frequency domain

- **Method**: joint-LSTM network to predict both direct plus early RIR and late RIR in frequency domain

Introduction: Reverberation

- A reverberant speech signal can be computed as the convolution of a clean speech signal s(t) with a room impulse response (RIR), h(t):

$$x(t) = s(t) * h(t)$$

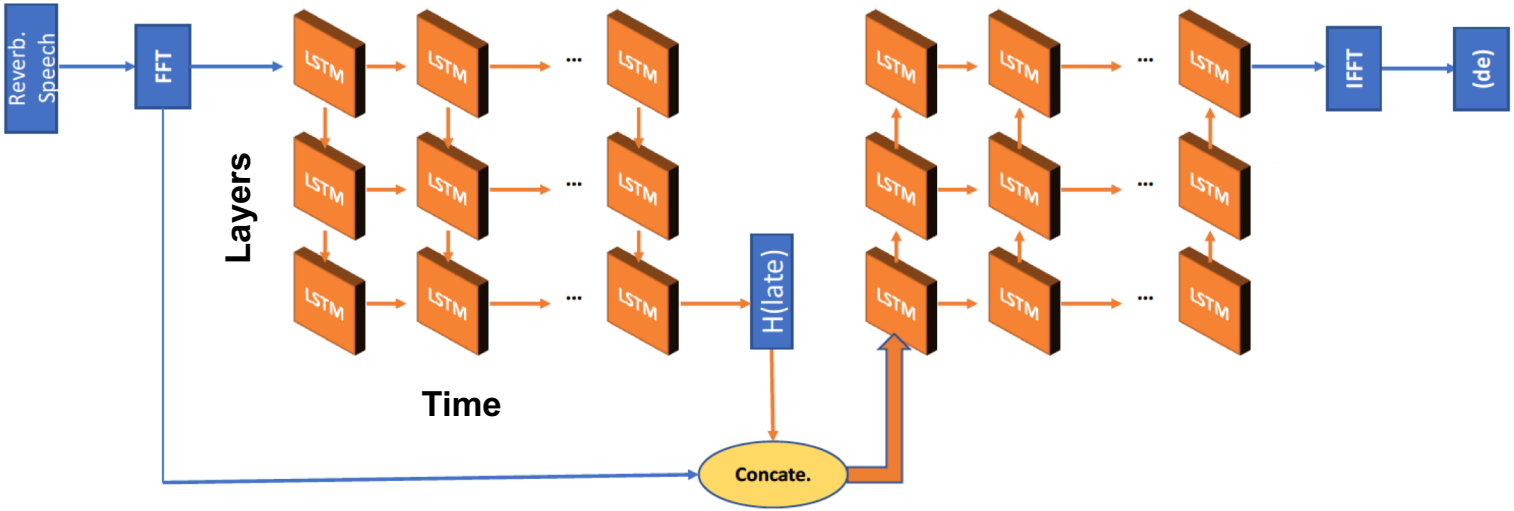
- RIR decomposed into direct, early and late:

$$h(t) = h_d(t) + h_e(t) + h_l(t)$$

- Reverberant signal is defined as direct sound plus early and late reflections:

$$x(t) = s(t) * h_d(t) + s(t) * h_e(t) + s(t) * h_l(t)$$

Network Architecture



Network Architecture

- The first part of the network predicts the late RIR in frequency domain
  - The number of neurons is set to 2048 for each LSTM layer
  - Three fully connected (FCN) layers

- The second part predicts the direct plus early RIR in frequency domain
  - The number of neurons is set to 4096 for first 2 LSTM layers
  - The number of neurons is set to 2048 for the last LSTM layer
  - Three FCN layers

- Rectified linear activation function used throughout
- Adam optimizer
- Learning rate: 0.0001
- Objective function: MSE

Features

- Given a time domain reverberant signal y(t)
  - Compute the 1024-point discrete Fourier transform (DFT)
  - Concatenate the real and imaginary components of the 1024-point DFT as input

$$Y(m) = \begin{bmatrix} Y_i\,(1)\; Y_i\,(2) \ldots Y_i\;(N) \\ Y_r\,(1)\; Y_r\,(2) \ldots Y_r\;(N) \end{bmatrix}$$

$$Y = \{Y(1)Y(2) \ldots Y(N_s)\}$$

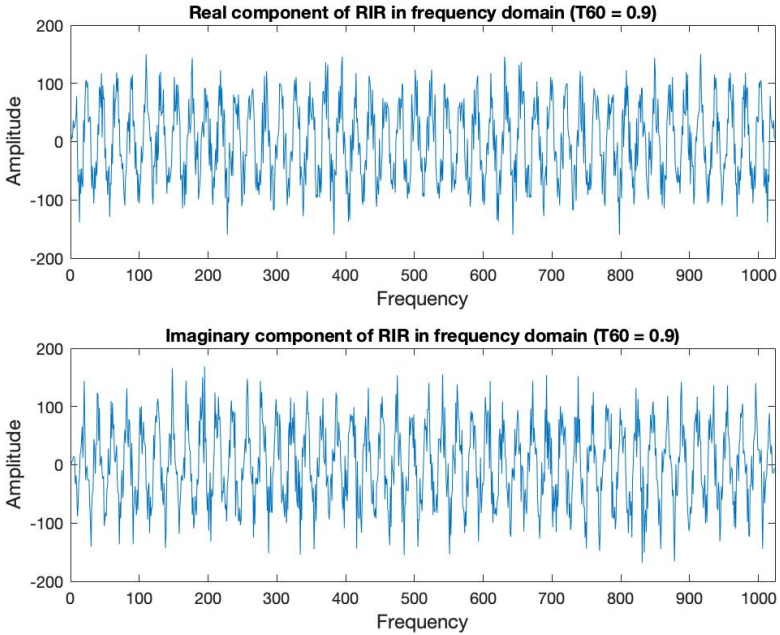
  - Most approaches ignore phase information
  - Recently, research has shown that including phase information improves results [3]
  - Our approach, given the real and imaginary components, means magnitude and phase information are addressed

Training Labels

- Predict transfer functions of the RIRs instead of speech:
  - Transform the direct plus early RIR ($h_{de}(t)$) and the late RIR ($h_l(t)$) into 1024- point DFTs (N = 1024)
  - Concatenate the real and imaginary components of the resulting DFT into one

$$H_l(m) = \{H_l(1)\, H_l(2) \ldots H_l(N)\}$$

$$H_{de}(m) = \{H_{de}(1)\, H_{de}(2) \ldots H_{de}(N)\}$$



Objective Function

- Trained using standard back propagation algorithm with mean-square error cost function

$$\frac{1}{2N}\sum_{f}\left[\left(\widehat{H}_{l}^{r}(f)-H_{l}^{r}(f)\right)^{2}+\left(\widehat{H}_{l}^{i}(f)-H_{l}^{i}(f)\right)^{2}\right]$$
$$+\frac{1}{2N}\sum_{f}\left[\left(\widehat{H}_{de}^{r}(f)-H_{de}^{r}(f)\right)^{2}+\left(\widehat{H}_{de}^{i}(f)-H_{de}^{i}(f)\right)^{2}\right]$$

- N is the input dimensions, which is 1024 units

Experiments

- Dataset: TIMIT corpus
- Randomly select 3000, 1000, and 1000 sentences to construct training, validation and testing datasets
- Simulate RIRs from 5 different rooms via image method [4]. The distance between the receiver and the speaker is set to 1m in all cases
- Select 3 different reverberation times: 0.3s, 0.6s and 0.9s
- 1500 different RIRs for training set, 500 different RIRs for validation set, and another 500 RIRs for testing set

Evaluation

- We convolve the estimated direct plus early RIR with clean speech, we call it estimated speech
- Compare the estimated speech with the true direct plus early speech signal
- Perceptual evaluation of speech quality (PESQ) [9]
  - PESQ score ranges from -0.5 to 4.5
- Short-Time Objective intelligibility (STOI) [10]
  - STOI measure ranges from 0 to 1
- Signal to distortion (SDR) [11]
  - No specific range
- Overall, higher values indicate better performance

Results

- SDR:
  - cIRM performs best at T_{60} of 0.3
  - Joint-LSTM outperforms the comparison approaches as the T_{60} increases
- STOI:
  - Proposed approaches has minor improvements compared with mixture, but not as good as cIRM and IRM
- PESQ:
  - Proposed approaches outperforms the baseline approaches
- Overall, our joint learning approaches perform better as T_{60} increases
- More noticeably, the results reveal that frequency-domain processing often outperforms T-F domain processing.

Table 1. Comparison with different approaches

	SDR (db)			STOI			PESQ		
	0.3	0.6	0.9	0.3	0.6	0.9	0.3	0.6	0.9
Mixture	-1.89	-2.98	-4.01	0.58	0.48	0.43	1.7	1.42	1.25
Joint FCN	7.69	7.23	8.03	**0.77**	0.66	0.67	**2.28**	2.02	2.11
Joint LSTM	7.53	**9.32**	**8.92**	0.60	0.64	0.68	2.12	**2.10**	**2.13**
cIRM [3]	**7.90**	7.32	7.95	0.73	**0.70**	**0.71**	**2.28**	2.03	2.09
IRM [2]	7.62	7.27	7.54	0.72	**0.70**	0.70	2.23	2.00	2.01
Spectral Mapping [1]	7.28	7.25	7.48	0.71	0.69	0.68	2.01	1.97	1.90

Conclusion

- Our approach managed to extract RIR frequency information and enhance the reverberant signal
- Our approach enhanced reverberant speech in the complex domain by handling both real and imaginary information
- Our approach deviates from recent methods by processing in the frequency domain
- The joint-learning method, by adding predicted late information to the network, helps to improve the direct sound plus early reflection that is hard to predict directly

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