

LEAP Submission to CHiME-6 ASR Challenge

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Abstract

This paper reports the LEAP submission to the CHiME-6 challenge. The CHiME-6 Automatic Speech Recognition (ASR) challenge Track 1 involved the recognition of speech in noisy and reverberant acoustic conditions in home environments with multiple-party interactions. For the challenge submission, the LEAP system used extensive data augmentation and a factorized time-delay neural network (TDNN) architecture. We also explored a neural architecture that interleaved the TDNN layers with LSTM layers. The submitted system improved the Kaldi recipe by 2% in terms of relative word-error-rate improvements.

Index Terms: ASR, Reverberation, Time Delay Neural Networks, Data Augmentation.

1. Introduction

Automatic speech recognition (ASR) systems find widespread use in applications like human-machine interface, virtual assistants, smart speakers etc, where the input speech is often reverberant and noisy. The degradation of the systems in presence of noise and reverberation continues to be a challenging problem due to the low signal to noise ratio [1]. For *e.g.* Peddinti *et al*, [2] reports a 75% rel. increase in word error rate (WER) when signals from a far-field array microphone are used in place of those from headset microphones in the ASR systems, both during training and testing. This degradation could be primarily attributed to reverberation artifacts [3, 4]. The availability of multi-channel signals can be leveraged for alleviating these issues as most of the real life far-field speech recordings are captured by a microphone array.

The presence of noise and reverberation in the far field speech signal degrades the performance of the ASR leading to increased Word Error Rates (WER). Many methods have focused on alleviating the degradation in the WER by using multi-channel microphones for far field speech recognition. The traditional approach to multi-channel far-field ASR combines all the available channels by beamforming [5] and then processes the resulting single channel signal effectively. Weighted Prediction Error (WPE) [6] is another classical signal processing technique used to remove reverberations from the far field signals.

For automatic speech recognition acoustic modeling, the most popular modeling approach is the use of time delay neural networks [2] that is trained with a lattice free maximum mutual information (MMI) criterion [7]. The lattice free MMI model enable sequence cost function training and the model performs an efficient approximation to simplify computations without any lattice construction. Further, another powerful tool for dealing with noisy and reverberant speech in ASR is the use of data augmentation [8].

The CHiME-6 represents the sixth version in a series of challenges attempting to address automatic speech recognition in realistic home environments [9]. The speech material was

elicited using a dinner party scenario with efforts taken to capture data that is representative of natural conversational speech. This paper summarizes the LEAP submission to the Track-1 of the CHiME-6 challenge.

In our submission, we extend the previous literature of using data augmentation with a factorized version of time-delay neural network [10]. In addition, we also explore the use of LSTM models in the factorized TDNN. The system description is given below followed by the section which reports the ASR results in the CHiME-6 development data.

2. The CHiME-6 challenge dataset

The dataset for CHiME-6 challenge is same as the dataset for CHiME-5 challenge. The dataset is made up of the recording of 20 separate dinner parties taking place in real homes. Recordings were made in kitchen, dining and living room areas with each phase lasting for a minimum of 30 mins. Each dinner party has 4 participants. Each party has been recorded with a set of 6 Microsoft Kinect devices and in-ear Soundman OKM II Classic Studio binaural microphones. Each Kinect device has a linear array of 4 sample-synchronised microphones. The data is split into training, development, and evaluation sets as follows.

The training set consist of 16 parties with 32 speakers in total. The number of utterances in the training set is 79,980 adding up to around 41 hours. Development set has 2 parties with 8 speakers and 7,440 utterances with nearly 4.5 hours of audio. Similarly 2 parties with 8 speakers and 11,028 utterances comprising of 5.1 hours of audio is used as the evaluation set.

3. Proposed system

The proposed system consists of a pre-processing step using guided source separation based beamforming. Acoustic Model consists of an 18 layer factorized time delay neural network (F-TDNN) trained with lattice free MMI cost function with L2 weight regularization and 15-fold data augmentation.

3.1. Guided Source Separation (GSS)

In the CHiME-6 challenge, clean uncorrupted speech is not available for training a mask estimating neural network [11] based beamformer. Here, one has to resort to unsupervised mask estimation techniques, which, *e.g.*, have been used in the context of Blind Source Separation (BSS) [12] employing spatial mixture models. In [13, 14] the BSS approach is modified to make efficient use of the available time and speaker annotations provided with the challenge data. The GSS outputs time-frequency masks, from these mask spatial covariance matrices are estimated, and from these matrices, in turn, the coefficients of the statistically optimum Minimum Variance Distortionless Response (MVDR) beamformer [15] are computed.

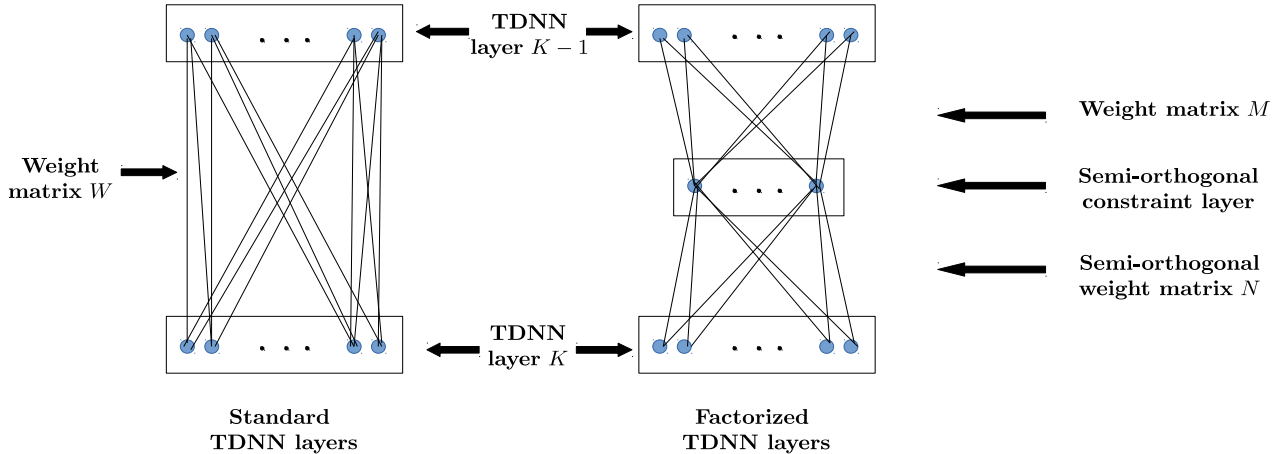


Figure 1: Standard TDNN and TDNN layers with semi-orthogonal weight constraint.

Table 1: Various model architectures and Word Error Rates (WER) % results for the CHiME-6 development set.

Models (layers)	S02 DINING	S02 Kitchen	S02 Living	S09 Dining	S09 Kitchen	S09 Living	Overall
Kaldi-Recipe-Results [9]	53.80	56.47	47.78	53.76	50.30	49.92	51.75
HMM-GMM	84.39	86.12	78.63	86.00	83.67	84.17	83.27
F-TDNN (15)	55.40	57.78	48.49	54.92	50.95	50.95	52.79
F-TDNN (18)	53.53	55.50	46.64	53.45	50.31	48.93	51.04
F-TDNN (18) LSTM (3)	56.80	59.79	49.91	57.68	52.65	53.42	54.65

3.2. Factorized Time Delay Neural Networks (F-TDNN)

Recently factorized typologies of conventional networks such as TDNN are suggested [10] as an improvement over TDNN-LSTM architectures with faster decoding. The basic idea is to factorize the weight matrix W of a TDNN layer into two matrices as $W = M \times N$. Here, N is constrained to be semi-orthogonal (a non-square matrix with orthogonal rows or columns). Figure 1 shows this difference more apparently. In our case, we trained the model with F-TDNN architecture with different number of layers and with data augmentation. The F-TDNN experiments used hidden layers of size 1536 with a bottleneck dimension of 160. In addition, we also explore an architecture of F-TDNN with a LSTM layer interleaved after every 5 layers of F-TDNN architecture. In the F-TDNN-LSTM implementation, the hidden dimension of TDNN layers was kept at 1024 with a bottleneck dimension of 160. The LSTM layers had a recurrent projection of 512 dimensions and non-recurrent projections of 512 dimensions. All the F-TDNN models also used a L2 weight regularization and were trained with LF-MMI cost function [7].

3.3. Data Augmentation

All the results for the F-TDNN models used a data augmentation of artificial room reverberation using 5 small and medium rooms [8]. In addition, a 3-way speed perturbation was also employed yielding 15 copies of the original training data.

4. Experiments and results

A mono-phone model is trained initially with MFCC features, using this a tri-phone model improved the WER. A tri-phone model with linear discriminant analysis (LDA) and maximum

likelihood linear transform (MLLT) is trained, which improved the performance. Finally, speaker adaptive training (SAT) is performed further improving the WER and is reported in Table 1 as HMM-GMM.

The WER results for various systems are reported in Table 1. As seen here, the WER results for F-TDNN model with 15 layers improved drastically over the HMM-GMM framework. This is further improved by the model with 18 layers. However, the inclusion of LSTM layers did not benefit the ASR performance. The final submitted system from the LEAP team was the F-TDNN (18 layer) model. This submitted system improved the Kaldi recipe by 2% in terms of relative word-error-rate improvements.

5. References

- [1] T. Hain, L. Burget, J. Dines, P. N. Garner, F. Grézl, A. El Hanani, M. Huijbregts, M. Karafiat, M. Lincoln, and V. Wan, "Transcribing meetings with the amida systems," *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 20, no. 2, pp. 486–498, 2012.
- [2] V. Peddinti, Y. Wang, D. Povey, and S. Khudanpur, "Low latency acoustic modeling using temporal convolution and LSTMs," *IEEE Signal Processing Letters*, 2017.
- [3] T. Yoshioka *et al.*, "Making machines understand us in reverberant rooms: Robustness against reverberation for automatic speech recognition," *IEEE Signal Processing Magazine*, vol. 29, no. 6, pp. 114–126, 2012.
- [4] K. Kinoshita *et al.*, "The reverb challenge: A common evaluation framework for dereverberation and recognition of reverberant speech," in *2013 IEEE WASPAA*. IEEE, 2013, pp. 1–4.
- [5] X. Anguera, C. Wooters, and J. Hernando, "Acoustic beamforming for speaker diarization of meetings," *IEEE Trans. Audio, Speech, Language Process.*, vol. 15, no. 7, pp. 2011–2022, 2007.

- [6] T. Nakatani, T. Yoshioka, K. Kinoshita, M. Miyoshi, and B.-H. Juang, "Speech dereverberation based on variance-normalized delayed linear prediction," *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 18, no. 7, pp. 1717–1731, 2010.
- [7] D. Povey, V. Peddinti, D. Galvez, P. Ghahremani, V. Manohar, X. Na, Y. Wang, and S. Khudanpur, "Purely sequence-trained neural networks for asr based on lattice-free mmi." in *Interspeech*, 2016, pp. 2751–2755.
- [8] T. Ko, V. Peddinti, D. Povey, M. L. Seltzer, and S. Khudanpur, "A study on data augmentation of reverberant speech for robust speech recognition," in *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2017, pp. 5220–5224.
- [9] J. B. E. V. Shinji Watanabe, Michael Mandel, "Sixth CHiME challenge - evaluation plan," Tech. Rep., 2020. [Online]. Available: <https://chimechallenge.github.io/chime6/>
- [10] D. Povey, G. Cheng, Y. Wang, K. Li, H. Xu, M. Yarmohammadi, and S. Khudanpur, "Semi-orthogonal low-rank matrix factorization for deep neural networks." in *Interspeech*, 2018, pp. 3743–3747.
- [11] J. Heymann, L. Drude, and R. Haeb-Umbach, "Neural network based spectral mask estimation for acoustic beamforming," in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2016, pp. 196–200.
- [12] D. H. T. Vu and R. Haeb-Umbach, "Blind speech separation employing directional statistics in an expectation maximization framework," in *2010 IEEE International Conference on Acoustics, Speech and Signal Processing*. IEEE, 2010, pp. 241–244.
- [13] C. Boeddeker, J. Heitkaemper, J. Schmalenstroerer, L. Drude, J. Heymann, and R. Haeb-Umbach, "Front-end processing for the chime-5 dinner party scenario," in *CHiME5 Workshop, Hyderabad, India*, 2018.
- [14] E. Vincent, N. Bertin, R. Gribonval, and F. Bimbot, "From blind to guided audio source separation: How models and side information can improve the separation of sound," *IEEE Signal Processing Magazine*, vol. 31, no. 3, pp. 107–115, 2014.
- [15] T. Higuchi, N. Ito, T. Yoshioka, and T. Nakatani, "Robust mvdr beamforming using time-frequency masks for online/offline asr in noise," in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2016, pp. 5210–5214.