Speech Technology: Frontiers and Applications

Hot Topics in Speech Recognition

Xiangang Li, Guoguo Chen

Outline

- Far-field speech recognition
- Mix-lingual speech recognition
- “Low resource” speech recognition
- Homework

Outline

- Far-field speech recognition
- Mix-lingual speech recognition
- “Low resource” speech recognition
- Homework

Far-field: the task

Siri released in 2011

Echo released in 2014

Far-field: the difficulties

- Low SNR
  - Background noise
  - Speaker playback
  - Microphone sensitivity

- High reverberation
  - Reflections
  - Diffusions

Reverberation Example. Clean signal, followed by different versions of reverberation (with longer and longer decay times).

Close talk example.

Far-field example.

Far-field: data augmentation

- The idea
  - Augments the training data as if it were collected in a far-field setting

- Methods
  - Reverb augmentation
  - Noise augmentation
  - Volume perturbation
  - Speed perturbation
  - Frequency masking
  - Time masking
  - …

Far-field: data augmentation

- The ASpIRE Challenge
    - IARPA’s challenge for far-field ASR
    - Training data: English portion of the Fisher database
    - Test data: collected in noisy and reverberant environments

- The challenges
    - Training/test mis-match
    - Unknown devices
    - Unknown acoustic space

Far-field: data augmentation

深蓝学院 shenlanxueyuan.com

- The ASpIRE Challenge
  - IARPA’s challenge for far-field ASR
  - Training data: English portion of the Fisher database
  - Test data: collected in noisy and reverberant environments

- The challenges
  - Training/test mis-match
  - Unknown devices
  - Unknown acoustic space

JHU ASPIRE SYSTEM : ROBUST LVCSR WITH TDNNS, IVECTOR ADAPTATION AND RNN-LMS

Vijayaditya Peddinti[1], *Guoguo Chen*[1], *Vimal Manohar*[1], *Tom Ko*[3] *Daniel Povey*[1,2], *Sanjeev Khudanpur*[1,2]

[1]Center for language and speech processing &
[2]Human Language Technology Center of Excellence
The Johns Hopkins University, Baltimore, MD 21218, USA
[3]Huawei Noah’s Ark Research Lab, Hong Kong, China
{vijay.p,guoguo,khudanpur}@jhu.edu, {vimal.manohar91, tomkocse, dpovey}@gmail.com

ABSTRACT

Multi-style training, using data which emulates a variety of possible test scenarios, is a popular approach towards robust acoustic modeling. However acoustic models capable of exploiting large amounts of training data in a comparatively short amount of training time are essential. In this paper we tackle the problem of reverberant speech recognition using 5500 hours of simulated reverberant data. We use time-delay neural network (TDNN) architecture, which is capable of tackling long-term interactions between speech and corrupting sources in reverberant environments. By sub-sampling the outputs at TDNN layers across time steps, training time is substantially reduced. Combining this with distributed-optimization we show that the TDNN can be trained in 3 days using up to 32 GPUs. Further, iVectors are used as an input to the neural network to perform instantaneous speaker and environment adaptation. Finally, recurrent neural network language models are applied to the lattices to further improve the performance. Our system is shown to provide state-of-the-art results in the IARPA ASpIRE challenge, with 26.5% WER on the *dev_test* set.

iVectors which capture both speaker and environment specific information have been shown to be useful for rapid adaptation of the neural network [4, 5, 6]. iVector based adaptation has also been shown to be effective in reverberant environments [7]. In this paper we use this adaptation technique.

We show experimental results on the ASpIRE far-field speech recognition challenge held by IARPA [8]. This challenge uses the English portion of the Fisher database [9] for acoustic and language model training. We show that in this large data scenario the proposed network architecture, combined with a distributed optimization technique [10], can train on multi-condition training data of ~ 5500 hours, using up to 32 GPUs, in 3 days.

Using the TDNN architecture helps us to achieve results close to those of the best combined system submitted to the ASpIRE challenge, while using only a single system. Our system was able to achieve 26.5% WER on the *dev-test* set, while the next best system achieved 27.2% WER [1].

The paper is organized as follows, Section 2 describes the acoustic model, Section 3 describes the language model, Section 4 analyses the results, and conclusions are presented in Section 5.

1. JHU ASpIRE system: robust LVCSR withTDNNs, ivector adaptation and RNN-LMs

Far-field: data augmentation

深蓝学院 shenlanxueyuan.com

- The ASpIRE Challenge
  - IARPA's challenge for far-field ASR
  - Training data: English portion of the Fisher database
  - Test data: collected in noisy and reverberant environments

- The challenges
  - Training/test mis-match
  - Unknown devices
  - Unknown acoustic space

JHU ASPIRE SYSTEM : ROBUST LVCSR WITH TDNNS, IVECTOR ADAPTATION AND RNN-LMS

Vijayaditya Peddinti[1], Guoguo Chen[1], Vimal Manohar[1], Tom Ko[3] Daniel Povey[1,2], Sanjeev Khudanpur[1,2]

[1]Center for language and speech processing &
[2]Human Language Technology Center of Excellence
The Johns Hopkins University, Baltimore, MD 21218, USA
[3]Huawei Noah's Ark Research Lab, Hong Kong, China
{vijay.p,guoguo,khudanpur}@jhu.edu, {vimal.manohar91, tomkocse, dpovey}@gmail.com

Reverberation robust acoustic modeling using i-vectors with time delay neural networks

Vijayaditya Peddinti[1], Guoguo Chen[1], Daniel Povey[1,2], Sanjeev Khudanpur[1,2]

[1]Center for language and speech processing &
[2]Human Language Technology Center of Excellence
The Johns Hopkins University, Baltimore, MD 21218, USA
{vijay.p,guoguo,khudanpur}@jhu.edu, dpovey@gmail.com

Abstract

In reverberant environments there are long term interactions between speech and corrupting sources. In this paper a time delay neural network (TDNN) architecture, capable of learning long term temporal relationships and translation invariant representations, is used for reverberation robust acoustic modeling. Further, iVectors are used as an input to the neural network to perform instantaneous speaker and environment adaptation, providing 10% relative improvement in word error rate. By subsampling the outputs at TDNN layers across time steps, training time is reduced. Using a parallel training algorithm we show that the TDNN can be trained on ~ 5500 hours of speech data in 3 days using up to 32 GPUs. The TDNN is shown to provide results competitive with state of the art systems in the IARPA ASpIRE challenge, with 27.7% WER on the dev_test set.

Index Terms: far field speech recognition, time delay neural

the input context up to 280 milliseconds. The ability to process such a wide temporal context enables the network to deal with late reverberations.

iVectors which capture both speaker and environment specific information have been shown to be useful for rapid adaptation of the neural network [7, 8, 9]. iVector based adaptation has also been shown to be effective in reverberant environments [10]. In this paper we use this adaptation technique.

We show experimental results on the ASpIRE far-field speech recognition challenge held by IARPA [11]. This challenge uses the English portion of the Fisher database [12] for acoustic and language model training. We show that in this large data scenario the proposed network architecture, combined with a parallel training technique [13], can train on multi-condition training data of ~ 5500 hours, using up to 32 GPUs, in 3 days.

Using the TDNN architecture helps us to achieve results close to those of the best combined system submitted to the AS-

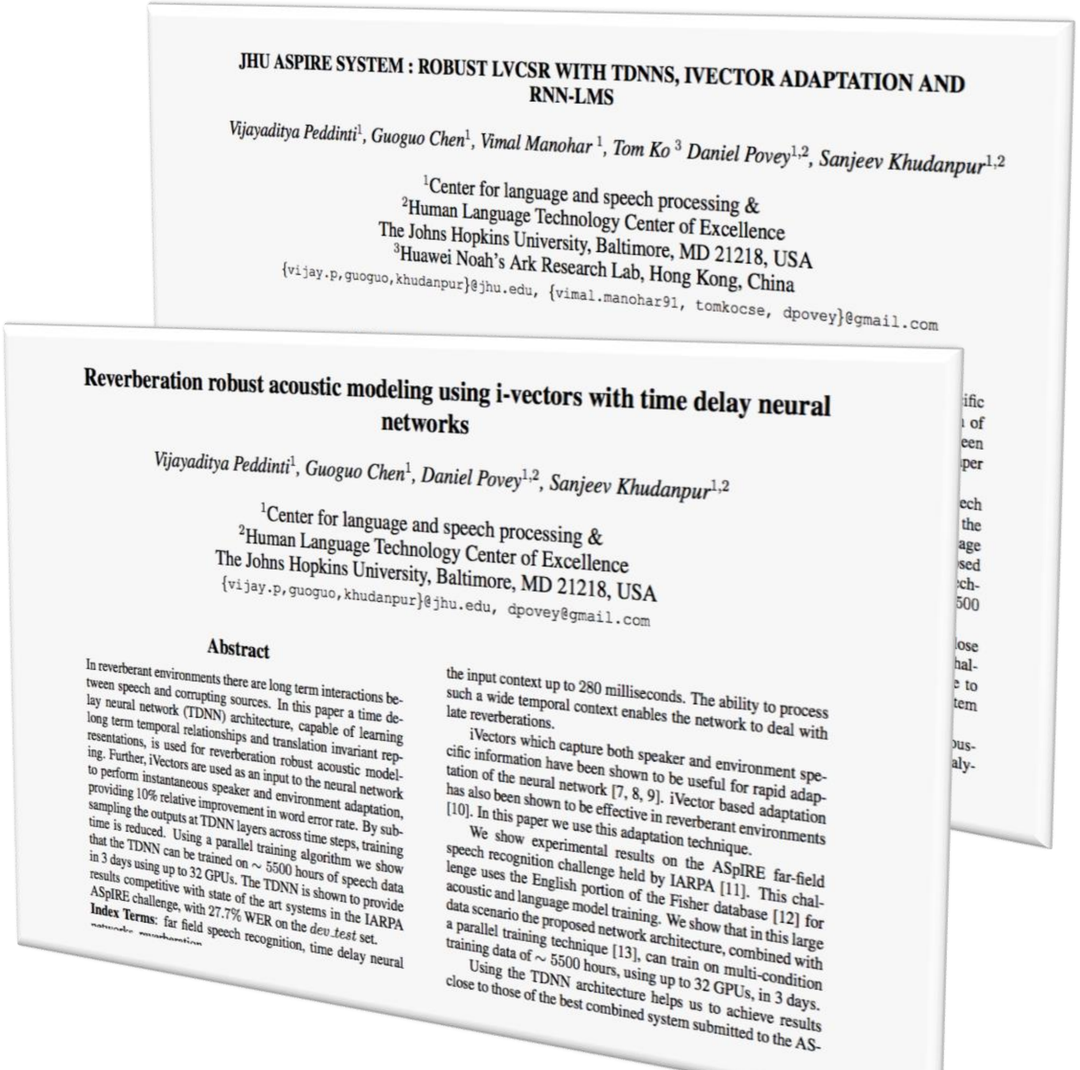
1. JHU ASpIRE system: robust LVCSR withTDNNs, ivector adaptation and RNN-LMs
2. Reverberation robust acoustic modeling using i-vectors with time delay neural networks

Far-field: data augmentation

Table 1: Comparison of input contexts and training data augmentation, used for training the TDNNs

Acoustic Model	context	training data	*dev* WER
TDNN A	[-13, 9]	clean	47.6
TDNN A	[-13, 9]	rvb	31.7
TDNN B	[-16, 12]	rvb	30.8
TDNN B	[-16, 12]	rvb + sp	31.0
TDNN C	[-22, 12]	rvb + sp	31.1
DNN	[-16, 12]	rvb	33.1

rvb : reverberation of training data using real world RIRs
sp : speech perturbation of data prior to reverberation



JHU ASPIRE SYSTEM : ROBUST LVCSR WITH TDNNS, IVECTOR ADAPTATION AND RNN-LMS

Vijayaditya Peddinti[1], Guoguo Chen[1], Vimal Manohar [1], Tom Ko [3] Daniel Povey[1,2], Sanjeev Khudanpur[1,2]

[1]Center for language and speech processing &
[2]Human Language Technology Center of Excellence
The Johns Hopkins University, Baltimore, MD 21218, USA
[3]Huawei Noah's Ark Research Lab, Hong Kong, China
{vijay.p,guoguo,khudanpur}@jhu.edu, {vimal.manohar91, tomkocse, dpovey}@gmail.com

Reverberation robust acoustic modeling using i-vectors with time delay neural networks

Vijayaditya Peddinti[1], Guoguo Chen[1], Daniel Povey[1,2], Sanjeev Khudanpur[1,2]

[1]Center for language and speech processing &
[2]Human Language Technology Center of Excellence
The Johns Hopkins University, Baltimore, MD 21218, USA
{vijay.p,guoguo,khudanpur}@jhu.edu, dpovey@gmail.com

Abstract

In reverberant environments there are long term interactions between speech and corrupting sources. In this paper a time delay neural network (TDNN) architecture, capable of learning long term temporal relationships and translation invariant representations, is used for reverberation robust acoustic modeling. Further, iVectors are used as an input to the neural network to perform instantaneous speaker and environment adaptation, providing 10% relative improvement in word error rate. By subsampling the outputs at TDNN layers across time steps, training time is reduced. Using a parallel training algorithm we show that the TDNN can be trained on ~ 5500 hours of speech data in 3 days using up to 32 GPUs. The TDNN is shown to provide results competitive with state of the art systems in the IARPA ASpIRE challenge, with 27.7% WER on the *dev_test* set.

Index Terms: far field speech recognition, time delay neural

the input context up to 280 milliseconds. The ability to process such a wide temporal context enables the network to deal with late reverberations.

iVectors which capture both speaker and environment specific information have been shown to be useful for rapid adaptation of the neural network [7, 8, 9]. iVector based adaptation has also been shown to be effective in reverberant environments [10]. In this paper we use this adaptation technique.

We show experimental results on the ASpIRE far-field speech recognition challenge held by IARPA [11]. This challenge uses the English portion of the Fisher database [12] for acoustic and language model training. We show that in this large data scenario the proposed network architecture, combined with a parallel training technique [13], can train on multi-condition training data of ~ 5500 hours, using up to 32 GPUs, in 3 days.

Using the TDNN architecture helps us to achieve results close to those of the best combined system submitted to the AS-

1. JHU ASpIRE system: robust LVCSR withTDNNs, ivector adaptation and RNN-LMs
2. Reverberation robust acoustic modeling using i-vectors with time delay neural networks

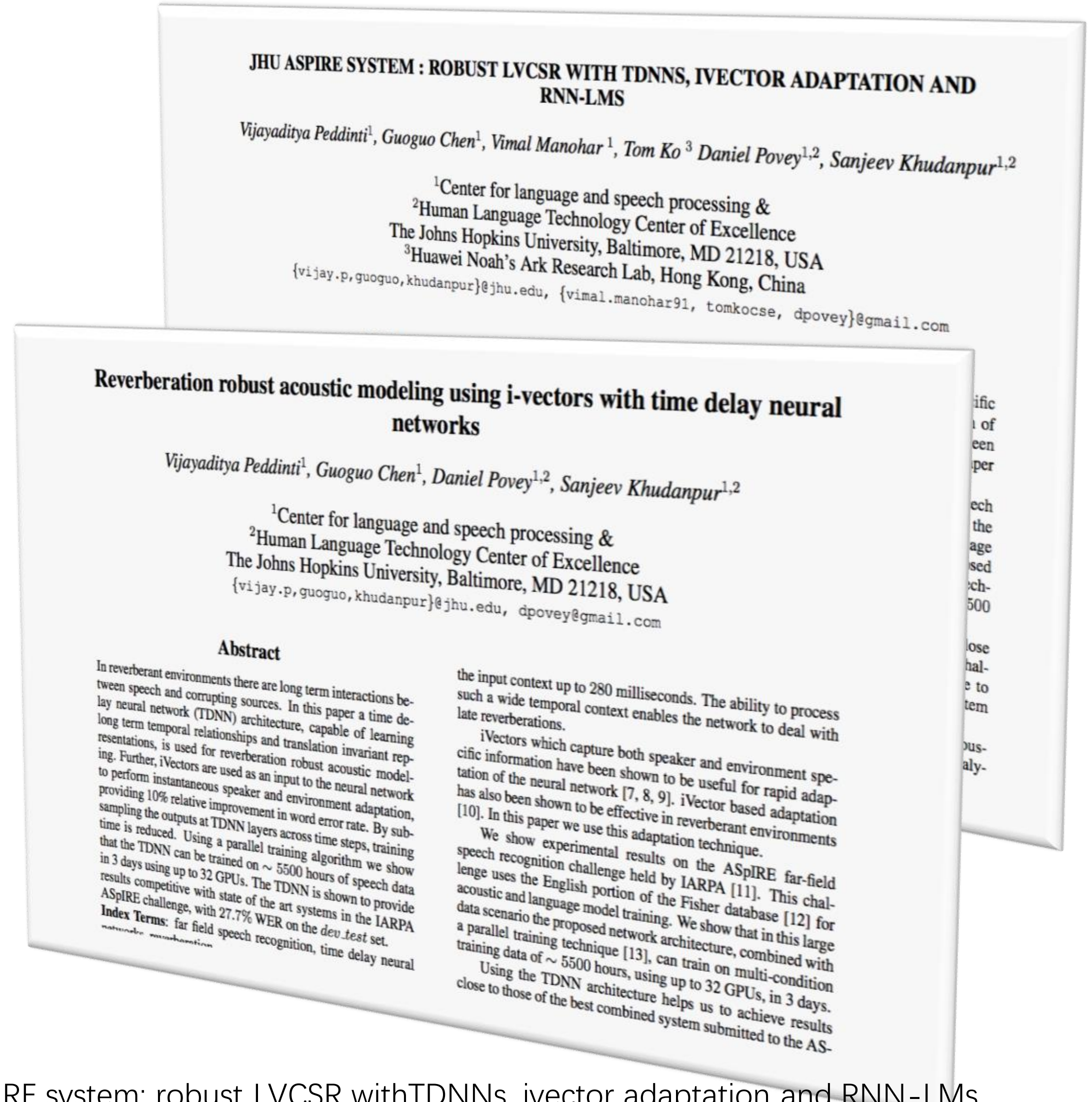
Far-field: data augmentation

深蓝学院
shenlanxueyuan.com

Table 2: Comparison of systems w/ & w/o volume perturbed training data and w/ & w/o volume normalized test data

Acoustic Model	Training Data	Test Data	*dev* WER
TDNN B	rvb		38.3
TDNN B	rvb	vol. norm.	30.8
TDNN B	rvb +vp		33.3
TDNN B	rvb +vp	vol. norm.	30.9

rvb : reverberation of training data using real world RIRs
vp : volume perturbation of data after reverberation


JHU ASPIRE SYSTEM : ROBUST LVCSR WITH TDNNS, IVECTOR ADAPTATION AND RNN-LMS

Vijayaditya Peddinti[1], Guoguo Chen[1], Vimal Manohar[1], Tom Ko[3] Daniel Povey[1,2], Sanjeev Khudanpur[1,2]

[1]Center for language and speech processing &
[2]Human Language Technology Center of Excellence
The Johns Hopkins University, Baltimore, MD 21218, USA
[3]Huawei Noah's Ark Research Lab, Hong Kong, China
{vijay.p,guoguo,khudanpur}@jhu.edu, {vimal.manohar91, tomkocse, dpovey}@gmail.com

Reverberation robust acoustic modeling using i-vectors with time delay neural networks

Vijayaditya Peddinti[1], Guoguo Chen[1], Daniel Povey[1,2], Sanjeev Khudanpur[1,2]

[1]Center for language and speech processing &
[2]Human Language Technology Center of Excellence
The Johns Hopkins University, Baltimore, MD 21218, USA
{vijay.p,guoguo,khudanpur}@jhu.edu, dpovey@gmail.com

Abstract

In reverberant environments there are long term interactions between speech and corrupting sources. In this paper a time delay neural network (TDNN) architecture, capable of learning long term temporal relationships and translation invariant representations, is used for reverberation robust acoustic modeling. Further, iVectors are used as an input to the neural network to perform instantaneous speaker and environment adaptation, providing 10% relative improvement in word error rate. By subsampling the outputs at TDNN layers across time steps, training time is reduced. Using a parallel training algorithm we show that the TDNN can be trained on ~ 5500 hours of speech data in 3 days using up to 32 GPUs. The TDNN is shown to provide results competitive with state of the art systems in the IARPA ASpIRE challenge, with 27.7% WER on the *dev_test* set.
Index Terms: far field speech recognition, time delay neural

the input context up to 280 milliseconds. The ability to process such a wide temporal context enables the network to deal with late reverberations.

iVectors which capture both speaker and environment specific information have been shown to be useful for rapid adaptation of the neural network [7, 8, 9]. iVector based adaptation has also been shown to be effective in reverberant environments [10]. In this paper we use this adaptation technique.

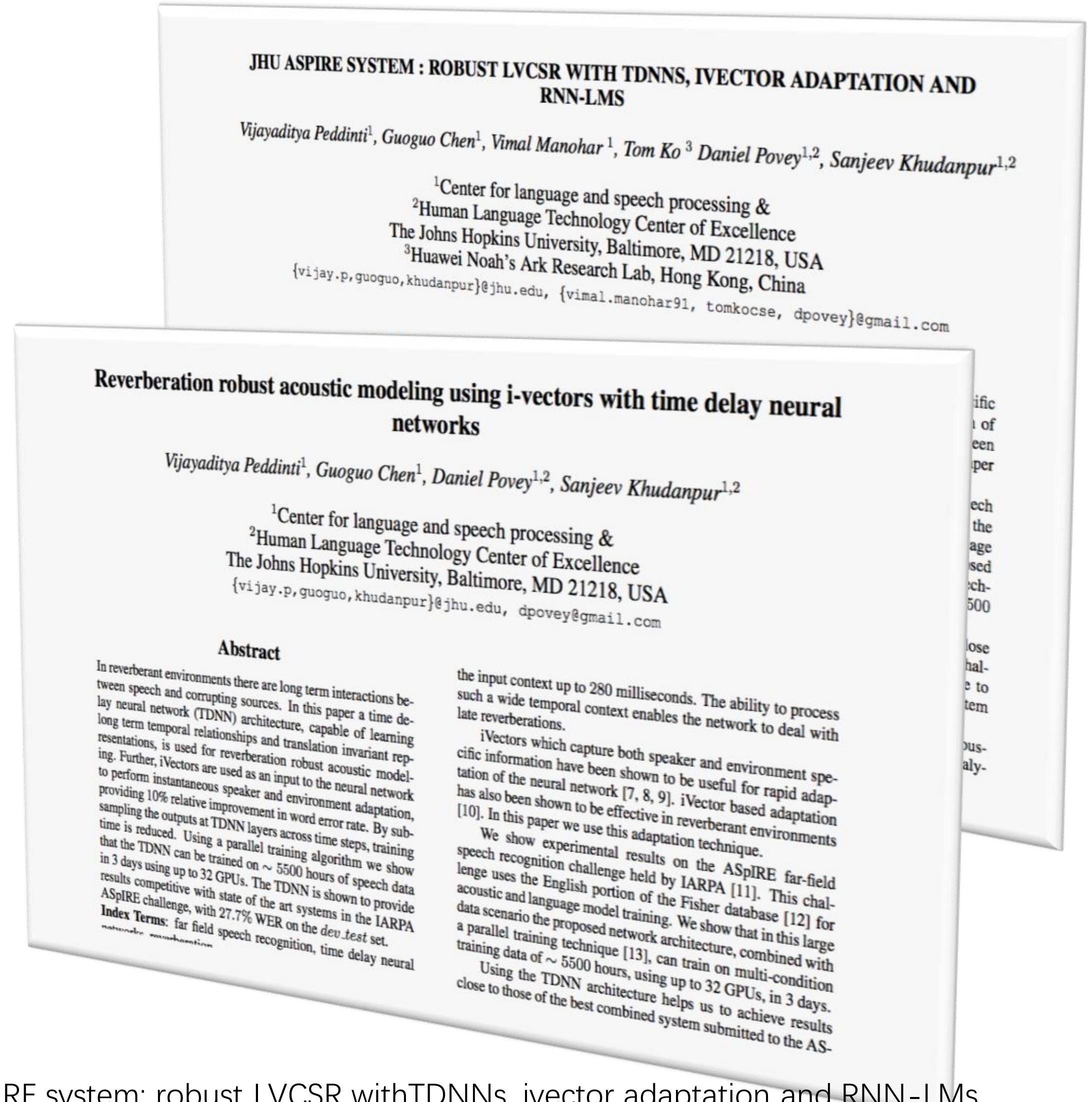
We show experimental results on the ASpIRE far-field speech recognition challenge held by IARPA [11]. This challenge uses the English portion of the Fisher database [12] for acoustic and language model training. We show that in this large data scenario the proposed network architecture, combined with a parallel training technique [13], can train on multi-condition training data of ~ 5500 hours, using up to 32 GPUs, in 3 days.

Using the TDNN architecture helps us to achieve results close to those of the best combined system submitted to the AS-

1. JHU ASpIRE system: robust LVCSR withTDNNs, ivector adaptation and RNN-LMs
2. Reverberation robust acoustic modeling using i-vectors with time delay neural networks

Far-field: data augmentation

- Other tricks
  - i-vector
  - RNNLM
  - Pronunciation modeling
  - Sequence training
  - ……



JHU ASPIRE SYSTEM : ROBUST LVCSR WITH TDNNS, IVECTOR ADAPTATION AND RNN-LMS

Vijayaditya Peddinti[1], Guoguo Chen[1], Vimal Manohar[1], Tom Ko[3] Daniel Povey[1,2], Sanjeev Khudanpur[1,2]

[1]Center for language and speech processing &
[2]Human Language Technology Center of Excellence
The Johns Hopkins University, Baltimore, MD 21218, USA
[3]Huawei Noah's Ark Research Lab, Hong Kong, China
{vijay.p,guoguo,khudanpur}@jhu.edu, {vimal.manohar91, tomkocse, dpovey}@gmail.com

Reverberation robust acoustic modeling using i-vectors with time delay neural networks

Vijayaditya Peddinti[1], Guoguo Chen[1], Daniel Povey[1,2], Sanjeev Khudanpur[1,2]

[1]Center for language and speech processing &
[2]Human Language Technology Center of Excellence
The Johns Hopkins University, Baltimore, MD 21218, USA
{vijay.p,guoguo,khudanpur}@jhu.edu, dpovey@gmail.com

Abstract

In reverberant environments there are long term interactions between speech and corrupting sources. In this paper a time delay neural network (TDNN) architecture, capable of learning long term temporal relationships and translation invariant representations, is used for reverberation robust acoustic modeling. Further, iVectors are used as an input to the neural network to perform instantaneous speaker and environment adaptation, providing 10% relative improvement in word error rate. By subsampling the outputs at TDNN layers across time steps, training time is reduced. Using a parallel training algorithm we show that the TDNN can be trained on ~ 5500 hours of speech data in 3 days using up to 32 GPUs. The TDNN is shown to provide results competitive with state of the art systems in the IARPA ASpIRE challenge, with 27.7% WER on the *dev_test* set.

Index Terms: far field speech recognition, time delay neural networks, reverberation

the input context up to 280 milliseconds. The ability to process such a wide temporal context enables the network to deal with late reverberations.

iVectors which capture both speaker and environment specific information have been shown to be useful for rapid adaptation of the neural network [7, 8, 9]. iVector based adaptation has also been shown to be effective in reverberant environments [10]. In this paper we use this adaptation technique.

We show experimental results on the ASpIRE far-field speech recognition challenge held by IARPA [11]. This challenge uses the English portion of the Fisher database [12] for acoustic and language model training. We show that in this large data scenario the proposed network architecture, combined with a parallel training technique [13], can train on multi-condition training data of ~ 5500 hours, using up to 32 GPUs, in 3 days.

Using the TDNN architecture helps us to achieve results close to those of the best combined system submitted to the AS-

1. JHU ASpIRE system: robust LVCSR withTDNNs, ivector adaptation and RNN-LMs
2. Reverberation robust acoustic modeling using i-vectors with time delay neural networks

Far-field: signal processing

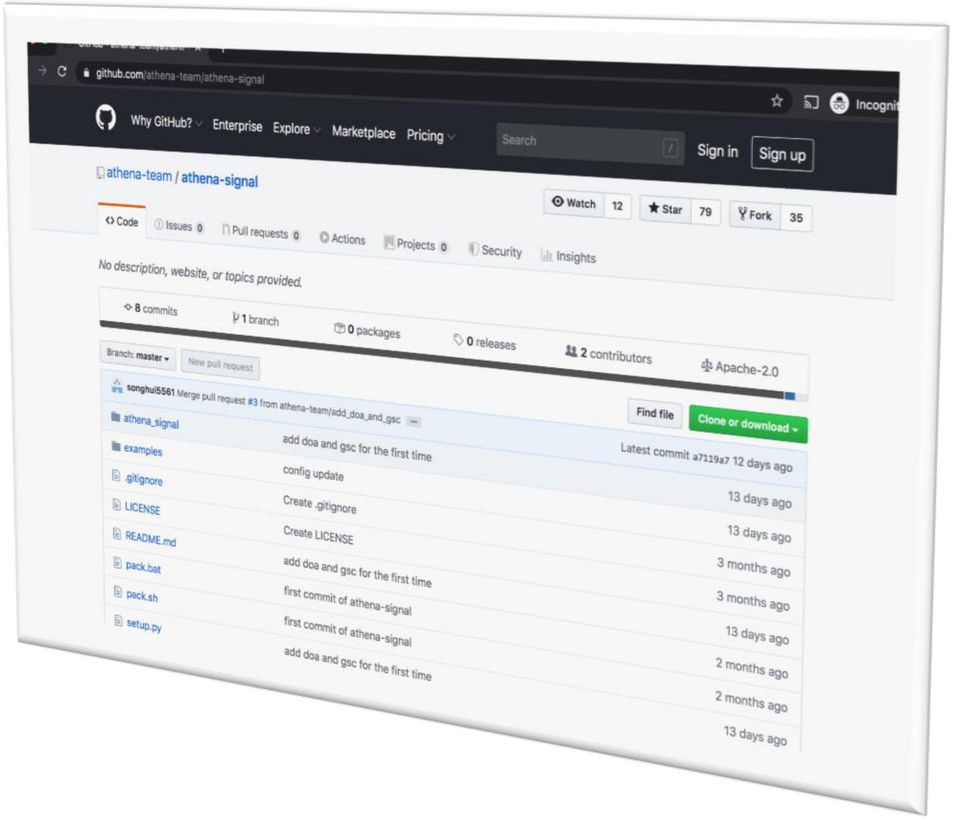
- The idea
  - Processes the input audio and improves the audio quality

- Methods
  - Acoustic echo cancellation (AEC)
  - Automatic gain control (AGC)
  - Beamforming (BF)
  - Noise suppression (NS)
  - ……

Far-field: signal processing

- The idea
  - Processes the input audio and improves the audio quality

- Methods
  - Acoustic echo cancellation (AEC)
  - Automatic gain control (AGC)
  - Beamforming (BF)
  - Noise suppression (NS)
  - ……



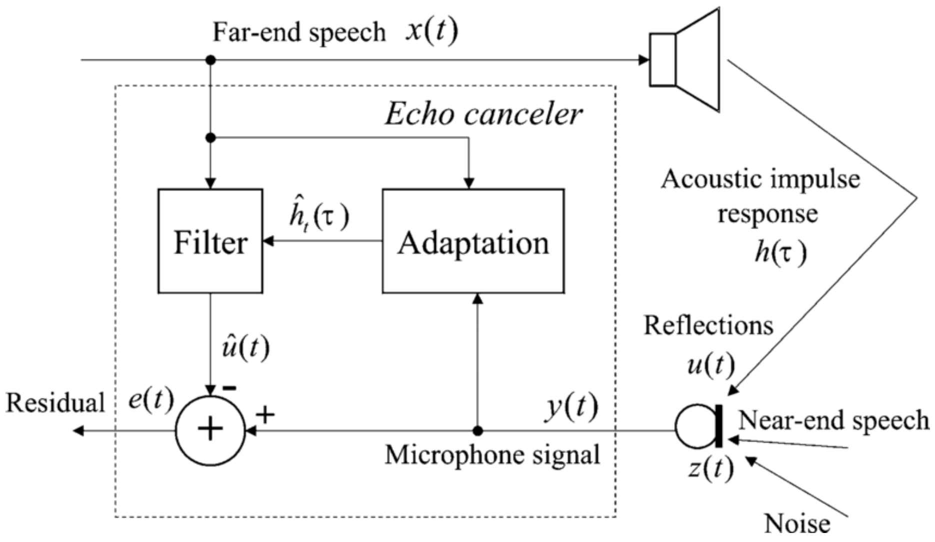
Athena signal: https://github.com/athena-team/athena-signal

Far-field: signal processing

深蓝学院 shenlanxueyuan.com

- Acoustic echo cancellation
  - Cancels acoustic feedback between a speaker and a microphone
  - Widely used in telecommunication
  - Necessary in smart speakers

- Technical details
  - Time delay estimation
  - Double-talk detection
  - Residual echo suppression
  - ……

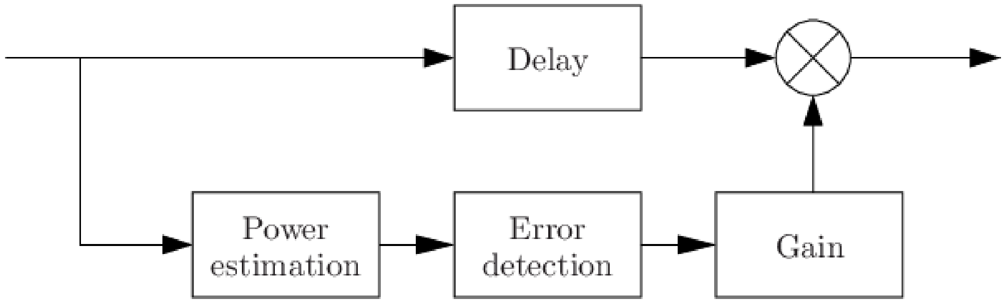


A typical AEC framework.

Photo credit: https://www.researchgate.net/

Far-field: signal processing

- Automatic gain control
  - Maintains a suitable signal amplitude at its output
  - Radio/Radar/Telephone ……
- Technical details
  - Gain factor calculation
  - Affects both signal and noise

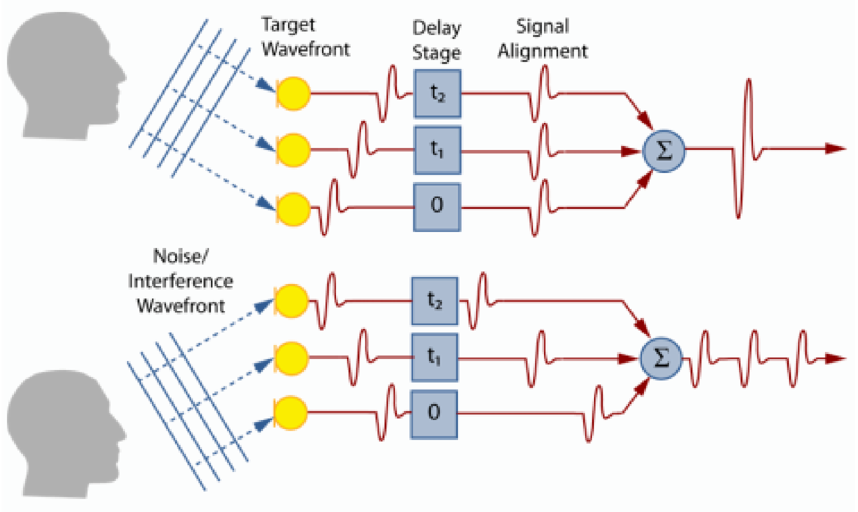


A typical AGC framework.

Photo credit: https://www.researchgate.net/

Far-field: signal processing

- Beamforming
  - Boosts SNR for a certain direction or source
  - Radio/Radar/Sonar……
- Technical details
  - A lot of different algorithms
  - Direction of arrival (DOA) estimation
  - ……



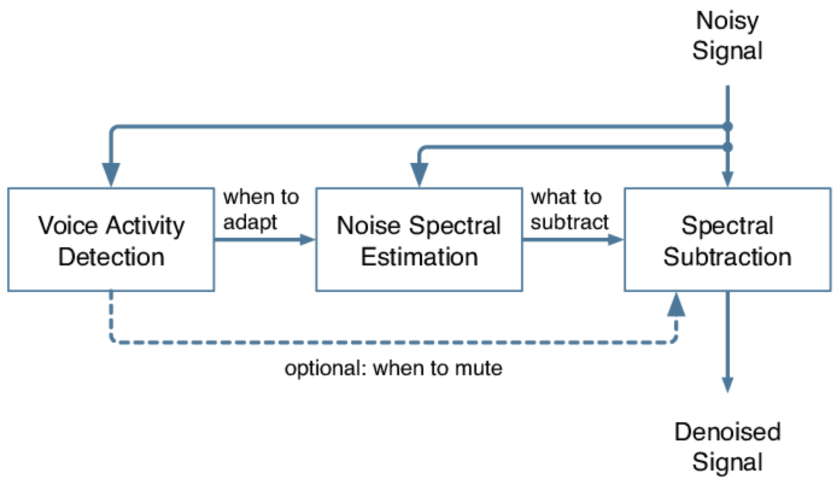
A typical delay-and-sum framework for beamforming.

Photo credit: https://beamforming-noise-cancellation.weebly.com/beamforming.html

Far-field: signal processing

- Noise suppression
  - Boosts speech SNR

- Technical details
  - A lot of different algorithms
  - Voice activities detection
  - Introduces distortion (bad impact on model)
  - ......



A typical noise suppression framework.

Photo credit: https://www.researchgate.net/

Far-field: signal processing

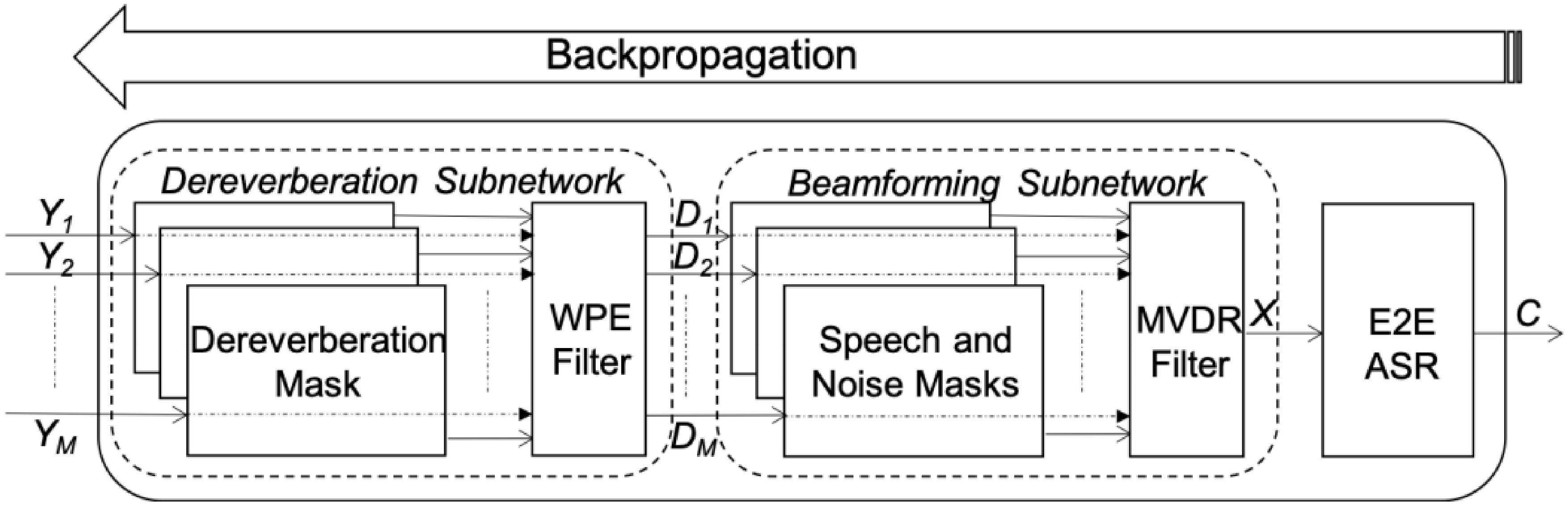
深蓝学院
shenlanxueyuan.com

- Combine signal processing and modeling
  - Directly connecting signal processing and the model usually leads to worse performance
  - Fine-tune the model parameters with the signal processing frontend
    - Collect new data with the signal processing frontend
    - Play and record existing data through the signal processing frontend

Far-field: end-to-end

- The idea
  - We have to fine-tune the ASR model with the signal processing frontend
  - Why don’t we train them jointly?

Far-field: end-to-end



End-to-end multichannel ASR architecture

Photo credit: [An Investigation of End-to-End Multichannel Speech Recognition for Reverberant and Mismatch Conditions]

Far-field: end-to-end

Method	*Dereverberation*	*Beamformer*			*REVERB Simulated*						*REVERB Real*		*DIRHA LA*
		Method	*Reference*	*Mask Type*	*Room 1*		*Room 2*		*Room 3*		*Room 1*		
					Near	*Far*	*Near*	*Far*	*Near*	*Far*	*Near*	*Far*	
Challenge baseline [6]	-	-	-	-	16.2	18.7	20.5	32.5	24.8	38.9	50.1	47.6	-
E2E Baseline	-	-	-	-	**5.4**	7.1	7.6	12.9	9.7	16.1	23.9	26.8	55.3
Pipeline	WPE	-	-	-	6.0	6.6	7.1	9.8	8.0	11.2	17.7	18.4	42.3
	DNN-WPE	-	-	-	5.7	6.0	7.5	9.3	7.8	10.1	16.4	18.5	41.3
	-	BeamformIt	X-Corr	-	5.8	6.1	**5.8**	8.5	6.9	10.2	14.6	16.1	39.2
	WPE	BeamformIt	X-Corr	-	6.6	5.9	6.1	7.0	6.8	8.2	11.3	11.9	**30.7**
	DNN-WPE	BeamformIt	X-Corr	-	6.3	**5.8**	6.4	**6.8**	**6.6**	**7.7**	**11.0**	**10.8***	31.3
E2E	WPE	-	-	-	6.3	6.7	6.7	8.9	7.4	10.6	17.0	19.8	42.3
	-	MVDR	Ch 2	TF	5.7	6.1	5.6	8.2	6.2	10.2	12.6	17.3	42.3
	-	MVDR	Ch 2	SAD	7.2	7.2	6.4	8.6	7.1	12.1	16.0	20.5	45.3
	WPE	MVDR	Ch 2	TF	**5.5**	**5.7***	**5.3***	**6.6***	6.5	**7.6***	10.7	13.7	35.4
	WPE	MVDR	Ch 2	SAD	8.3	7.8	6.9	7.0	7.6	8.6	10.8	13.9	31.6
	WPE	MVDR	Attention	SAD	6.4	6.3	5.9	6.8	**6.3***	**7.6***	**8.7***	**12.4**	**29.1***
Tachioka et. al. [31]	Spectral subtraction	Delay-sum	-	-	5.0	5.6	5.6	8.2	5.7	10.5	16.9	20.3	-
Alam et. al. [32]	Iterative deconvolution	-	-	-	6.7	7.3	8.0	11.1	8.1	12.1	21.4	22.0	-
Wang et. al. [10]	-	-	-	-	-	-	-	-	-	-	-	-	35.1

WER (%) on REVERB and DIRHA-WSJ (LA array) evaluation sets. Pipeline represents the traditional system where you have separate components for signal processing frontend and model, while E2E represents the end-to-end system.

Photo credit: [An Investigation of End-to-End Multichannel Speech Recognition for Reverberant and Mismatch Conditions]

Far-field: end-to-end

- Remarks
  - Neural frontend, and end-to-end approaches are giving very promising results
  - Traditional signal processing frontend is still heavily used in industry production systems
  - Trend of end-to-end solutions in some industry production systems

Outline

- Far-field speech recognition
- Mix-lingual speech recognition
- “Low resource” speech recognition
- Homework

Mix-lingual: definition

- Multi-lingual
  - Combines data from multiple languages to improve ASR performance
- Cross-lingual
  - Uses data from one or multiple languages to create ASR system for a different language
- Mix-lingual
  - Mixed language for a single ASR system, e.g., “我经常阅读paper”

Mix-lingual: a practical issue

- Code-mixing v.s. code-switching
  - Code-mixing: mixing the lexicons of two or more languages together
  - Code-switching: completely switching from one language's lexicon to another
- Code-mixing
  - 我想听 yesterday once more
  - 我朋友在 Google 工作
  - 我收到的验证码是 ABC123
- Important for Chinese ASR in production systems

Mix-lingual: a typical ZH/EN mix system

- Mixed phone set
  - English phones
    - Vowels, English-specific consonants
  - Chinese phones
    - Tonal vowels, Chinese-specific consonants
  - Shared phones
    - Shared consonants
  - Non-speech phones
    - SIL, SPN, NSN, etc.

- Valuable resource
  - CMU dictionary

Mix-lingual: a typical ZH/EN mix system

- Mixed lexicon
  - Pronunciation for English words
    - CMU dictionary
    - Spelled words (APP, API, etc)
    - Pronunciation generation (G2P)
  - Pronunciation for Chinese words
    - Existing dictionary (e.g., Pinyin based)
    - Words/characters lookup

- Valuable resource
  - Phonetisaurus: a grapheme-to-phoneme (G2P) toolkit

Mix-lingual: ASRU Code-mix Eval

- Organized by Datatang
- Mandarin Chinese and English, 16kHz, cellphone speech
- Training data
  - 500h Mandarin Chinese speech
  - 200h code-mix speech
  - 960h Librispeech 960h
- Official trigram LM (1M vocab)
- Two dev sets, each 20h
- One test set, 20h

Mix-lingual: ASRU Code-mix Eval

- Track1: (500h+200h+960h) AM training, fixed official LM, traditional speech recognition
- Track2: (500h+200h+960h) AM training, additional LM training data allowed, traditional speech recognition
- Track3: (500h+200h+960h) AM training, fixed official LM, end-to-end speech recognition
- MER (mixed error rate) = CER for Chinese, WER for English

Mix-lingual: ASRU Code-mix Eval

MER	Track1 (Fixed LM)	Track2 (Additional LM)	E2E (Fixed LM)
Team1	4.94%	4.72%	N/A
Team2	5.05%	5.64%	10.96%
Team3	5.28%	N/A	N/A
Team4	5.74%	5.80%	N/A
Team5	N/A	N/A	5.91%
Team6	N/A	N/A	8.82%
Team7	6.61%	5.88%	9.00%
Team8	N/A	N/A	9.37%

ASRU 2019 code-mix evaluation results

Outline

- Far-field speech recognition
- Mix-lingual speech recognition
- “Low resource” speech recognition
- Homework

Low-resource: definition

- Low computation resource?
  - Training?
  - Decoding?

- Low data resource?
  - Hours of data?
  - Tens of hours of data?
  - Hundreds of hours of data?

Low-resource: a practical view

- A new language or a new domain
- Manually transcribed data: < 500 hours
- How can we improve our system performance?

Low-resource: data augmentation

- Noise augmentation
- Volume perturbation
- Speed perturbation
- Frequency masking
- Time masking
- ……

Low-resource: data augmentation

System	Fold	Epochs	LM	SWB	CHE	Total
Baseline	1	6	fg	13.7	27.7	20.7
VTLP	3	2	fg	13.1	26.5	19.9
VTLP	5	2	fg	13.2	26.7	20.0
VTLP + time-warp	3	2	fg	13.3	26.8	20.1
Tempo-perturbed	3	2	fg	13.5	27.0	20.3
Speed-perturbed	3	2	fg	13.1	26.1	19.7
Speed-perturbed	3	6	fg	12.9	25.7	19.3

Results (% WER) for the baseline and speed-perturbed DNN systems on the subsets of the Hub5 00 evaluation set

Photo credit: [Audio Augmentation for Speech Recognition]

Low-resource: transfer learning

- Multi-lingual
- Domain adaptation

Low-resource: unsupervised learning

- Traditional unsupervised learning
- Masked Predictive Coding (MPC) based unsupervised learning

Outline

- Far-field speech recognition
- Mix-lingual speech recognition
- “Low resource” speech recognition
- Homework

Thanks!