Robust Automatic Speech Recognition
In the 21st Century

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Robust speech recognition

- As speech recognition is transferred from the laboratory to the marketplace robust recognition is becoming increasingly important

- “Robustness” in 1985:
  - Recognition in a quiet room using desktop microphones

- Robustness in 2014:
  - Recognition ....
    » over a cell phone
    » in a car
    » with the windows down
    » and the radio playing
    » at highway speeds
What I would like to do today

- Review background and motivation for current work:
  - Sources of environmental degradation

- Discuss selected approaches and their performance:
  - Traditional statistical parameter estimation
  - Missing feature approaches
  - Microphone arrays
  - Physiologically- and perceptually-motivated signal processing

- Comment on current progress for the hardest problems
Some of the hardest problems in speech recognition

- Speech in high noise (Navy F-18 flight line)
- Speech in background music
- Speech in background speech
- Transient dropouts and noise
- Spontaneous speech
- Reverberated speech
- Vocoded speech
Challenges in robust recognition

- **“Classical” problems:**
  - Additive noise
  - Linear filtering

- **“Modern” problems:**
  - Transient degradations
  - Much lower SNR

- **“Difficult” problems:**
  - Highly spontaneous speech
  - Reverberated speech
  - Speech masked by other speech and/or music
  - Speech subjected to nonlinear degradation
Solutions to classical problems: joint statistical compensation for noise and filtering

- Approach of Acero, Liu, Moreno, and Raj, et al. (1990-1997)...

“Clean” speech $x[m]$  

![Diagram showing linear filtering and additive noise](image)

- Compensation achieved by estimating parameters of noise and filter and applying inverse operations

- Interaction is nonlinear:

$$z = x + q + \log \left( 1 + e^{n-x-q} \right)$$
"Classical" combined compensation improves accuracy in stationary environments

- Threshold shifts by ~7 dB
- Accuracy still poor for low SNRs
But model-based compensation does not improve accuracy (much) in transient noise

Possible reasons: nonstationarity of background music and its speechlike nature
Summary: traditional methods

- The effects of additive noise and linear filtering are nonlinear
- Methods such as CDCN and VTS can be quite effective, but …
- … these methods require that the statistics of the received signal remain stationary over an interval of several hundred ms
Introduction: Missing-feature recognition

- Speech is quite intelligible, even when presented only in fragments

- Procedure:
  - Determine which time-frequency components appear to be unaffected by noise, distortion, etc.
  - Reconstruct signal based on “good” components

- A monaural example using “oracle” knowledge:
  - Mixed signals -
  - Separated signals -
Missing-feature recognition

**General approach:**
- Determine which cells of a spectrogram-like display are unreliable (or “missing”)
- Ignore missing features or make best guess about their values based on data that are present

**Comment:**
- Most groups (following the University of Sheffield) modify the internal representations to compensate for missing features
- We attempt to infer and replace missing components of input vector
Example: an original speech spectrogram
Spectrogram corrupted by noise at SNR 15 dB

Some regions are affected far more than others
Ignoring regions in the spectrogram that are corrupted by noise

- All regions with SNR less than 0 dB deemed missing (dark blue)
- Recognition performed based on colored regions alone
Recognition accuracy using compensated cepstra, speech in white noise (Raj, 1998)

- Large improvements in recognition accuracy can be obtained by reconstruction of corrupted regions of noisy speech spectrograms.
- A \textit{priori} knowledge of locations of “missing” features needed.
Recognition accuracy using compensated cepstra, speech corrupted by music

Recognition accuracy increases from 7% to 69% at 0 dB with cluster-based reconstruction
Practical recognition error: white noise (Seltzer, 2000)

Speech plus white noise:

Recognition Accuracy vs. SNR

Accuracy (%)

SNR (dB)

Oracle Masks
Bayesian Masks
Energy-based Masks
Baseline
Practical recognition error: background music

Speech plus music:

Recognition Accuracy vs. SNR

- Oracle Masks
- Bayesian Masks
- Energy-based Masks
- Baseline

Graph shows the effect of SNR on recognition accuracy for different methods.
Summary: Missing features

- Missing feature approaches can be valuable in dealing with the effects of transient distortion and other disruptions that are localized in the spectro-temporal display.

- The approach can be effective, but it is limited by the need to determine correctly which cells in the spectrogram are missing, which can be difficult in practice.
The problem of reverberation

- Comparison of single channel and delay-and-sum beamforming (WSJ data passed through measured impulse responses):

![Graph showing WER vs. Reverb time for single channel and delay-and-sum beamforming.](image-url)
Use of microphone arrays: motivation

- Microphone arrays can provide directional response, accepting speech from some directions but suppressing others.
Another reason for microphone arrays ...

- Microphone arrays can focus attention on the direct field in a reverberant environment
There are many ways we can use multiple microphones to improve recognition accuracy:

- Fixed delay-and-sum beamforming
- Microphone selection techniques
- Traditional adaptive filtering based on minimizing waveform distortion
- Feature-driven adaptive filtering (LIMABEAM)
- Statistically-driven separation approaches (ICA/BSS)
- Binaural processing based on selective reconstruction (e.g. PDCW)
- Binaural processing for correlation-based emphasis (e.g. Polyaural)
- Binaural processing using precedence-based emphasis (peripheral or central, e.g. SSF)
Delay-and-sum beamforming

- Simple processing based on equalizing delays to sensors and summing responses
- High directivity can be achieved with many sensors
- Baseline algorithm for any multi-microphone experiment
Adaptive array processing

- MMSE-based methods (e.g. LMS, RLS) falsely assume independence of signal and noise; not true in reverberation
  - Not as much of an issue with modern methods using objective functions based on kurtosis or negative entropy

- Methods reduce signal distortion, not error rate
Speech recognition using microphone arrays has been always been performed by combining two independent systems.

This is not ideal:
- Systems have different objectives
- Each system does not exploit information available to the other
Feature-based optimal filtering (Seltzer 2004)

- Consider array processing and speech recognition as part of a single system that shares information.
- Develop array processing algorithms specifically designed to improve speech recognition.

![Diagram showing array processing and ASR with MICs connected to array processing, which feeds into feature extraction and then ASR.]
Multi-microphone compensation for speech recognition based on cepstral distortion

- Multi-mic compensation based on optimizing speech features rather than signal distortion

Speech in Room  Delay and Sum  Optimal Comp
Sample results

- WER vs. SNR for WSJ with added white noise:
  - Constructed 50-point filters from calibration utterance using transcription only
  - Applied filters to all utterances
“Nonlinear beamforming:” reconstructing sound from fragments

Procedure:

- Determine which time-frequency components appear to be dominated by the desired signal
- Recognize based on subset of features that are “good”

OR

- Reconstruct signal based on “good” components and recognize using traditional signal processing
- In binaural processing determination of “good” components is based on estimated ITD
Assume two sources with known azimuths

Extract ITDs in TF rep (using zero crossings, cross-correlation, or phase differences in frequency domain)

Estimate signal amplitudes based on observed ITD (in binary or continuous fashion)

(Optionally) fill in missing TF segments after binary decisions
Audio samples using selective reconstruction

LEFT "EAR"
Filter Bank

Short-Time Fourier Analysis

Component Selection Based on ITD

(Optional) Missing Feature Reconstruction

Combine Channels

Enhanced Speech

RT60 (ms) 300
No Proc
Delay-sum
PDCW
Selective reconstruction from two mics helps

Examples using the PDCW algorithm (Kim et al. Interspeech 2009):

- Speech in “natural” noise:
- Reverberated speech:

Comment: Use of two mics provides substantial improvement that is typically independent of what is obtained using other methods.
Comparing linear and “nonlinear” beamforming

“Nonlinear beampatterns:

Linear beampattern:

**SNR = 0 dB**

**SNR = 20 dB**

**Comments:**

- Performance depends on SNR as well as source locations
- More consistent over frequency than linear beamforming

(Moghimi, ICASSP 2014)
Linear and nonlinear beamforming as a function of the number of sensors

(Moghimi & Stern, Interspeech 2014)
The binaural precedence effect

- Basic stimuli of the precedence effect:

- Localization is typically dominated by the first arriving pair
- Precedence effect believed by some (e.g. Blauert) to improve speech intelligibility
- Generalizing, we might say that onset enhancement helps at any level
Performance of onset enhancement in the SSF algorithm (Kim and Stern, Interspeech 2010)

- **Background music:**
- **Reverberation:**

**Comment:** Onset enhancement using SSF processing is especially effective in dealing with reverberation.
Combining onset enhancement with two-microphone processing:

- **Comment:** the use of both SSF onset enhancement and binaural comparison is especially helpful for improving WER for reverberated speech

(Park et al., Interspeech 2014)
Summary: use of multiple mics

- Microphone arrays provide directional response which can help interfering sources and in reverberation.
- Delay-and-sum beamforming is very simple and somewhat effective.
- Adaptive beamforming provides better performance but not in reverberant environments with MMSE-based objective functions.
- Adaptive beamforming based on minimizing feature distortion can be very effective but is computationally costly.
- For only two mics, “nonlinear” beamforming based on selective reconstruction is best.
- Onset enhancement helps a great deal as well in reverberance.
Auditory-based representations

What the speech recognizer sees:

An original spectrogram:                Spectrum “recovered” from MFCC:
Comments on MFCC representation

- It’s very “blurry” compared to a wideband spectrogram!

- Aspects of auditory processing represented:
  - Frequency selectivity and spectral bandwidth (but using a constant analysis window duration!)
    » Wavelet schemes exploit time-frequency resolution better
  - Nonlinear amplitude response (via log transformation only)

- Aspects of auditory processing NOT represented:
  - Detailed timing structure
  - Lateral suppression
  - Enhancement of temporal contrast
  - Other auditory nonlinearities
Physiologically-motivated signal processing: the Zhang-Carney-Zilany model of the periphery

- We used the “synapse output” as the basis for further processing.
An early evaluation by Kim et al. (Interspeech 2006)

- Synchrony response is smeared across frequency to remove pitch effects
- Higher frequencies represented by mean rate of firing
- Synchrony and mean rate combined additively
- Much more processing than MFCCs, but will simplify if results are useful
Comparing auditory processing with cepstral analysis: clean speech
Comparing auditory processing with cepstral analysis: 20-dB SNR
Comparing auditory processing with cepstral analysis: 10-dB SNR
Comparing auditory processing with cepstral analysis: 0-dB SNR
Auditory processing is more effective than MFCCs at low SNRs, especially in white noise.

Accuracy in background noise: Accuracy in background music:

[Results from Kim et al., Interspeech 2006]
But do auditory models really need to be so complex?

- Model of Zhang et al. 2001:

A much simpler model:

- Gammatone Filters
- Nonlinear Rectifiers
- Lowpass Filters
Comparing simple and complex auditory models

- Comparing MFCC processing, a trivial (filter–rectify–compress) auditory model, and the full Carney-Zhang model:

![Graph comparing applied performance of different auditory models](image-url)
Aspects of auditory processing we have found to be important in improving WER in noise

- The shape of the peripheral filters
- The shape of the auditory nonlinearity
- The use of “medium-time” analysis for noise and reverberation compensation
- The use of nonlinear filtering to obtain noise suppression and general separation of speechlike from non-speechlike signals (a form of modulation filtering)
- The use of nonlinear approaches to effect onset enhancement
- Binaural processing for further enhancement of target signals
PNCC processing (Kim and Stern, 2010, 2014)

- A pragmatic implementation of a number of the principles described:
  - Gammatone filterbanks
  - Nonlinearity shaped to follow auditory processing
  - “Medium-time” environmental compensation using nonlinearity cepstral highpass filtering in each channel
  - Enhancement of envelope onsets
  - Computationally efficient implementation
PNCC: an integrated front end based on auditory processing

Initial processing
- Pre-Emphasis
- STFT
- Magnitude Squared
- Triangular Frequency Integration
- Nonlinear Compression
- RASTA Filtering
- Nonlinear Expansion
- Logarithmic Nonlinearity
- DCT
- Mean Normalization
- MFCC Coefficients

Environmental compensation
- Medium-Time Power Calculation
- Asymmetric Noise Suppression with Temporal Masking
- Weight Smoothing
- $\tilde{Q}(m,l)$
- $\bar{K}(m,l)$
- $\tilde{S}(m,l)$
- $T(m,l)$
- $U(m,l)$
- $V(m,l)$

Final processing
- Mean Power Normalization
- Power Function Nonlinearity ($^{\gamma_1}$)
- Time-Frequency Normalization
- IDFT
- LPC-Based Cepstral Recursion
- MFCC Coefficients
- RASTA-PLP Coefficients
- PNCC Coefficients
Computational complexity of front ends

Mults & Divs per Frame

- MFCC
- PLP
- PNCC
- Truncated PNCC
Performance of PNCC in white noise (RM)
Performance of PNCC in white noise (WSJ)
Performance of PNCC in background music

[Graph showing the performance of PNCC, MFCC, MFCC with VTS, and RASTA–PLP in background music noise]
Performance of PNCC in reverberation

WSJ0–5k (Reverberation)

Accuracy (100 – WER)

Reverberation Time (s)

- PNCC
- MFCC with VTS
- MFCC
- RASTA–PLP
Contributions of PNCC components: white noise (WSJ)

WSJ0–5k (White Noise)

Accuracy (100 - WER) vs SNR (dB)

- Blue triangle: + Temporal masking
- Green triangle: + Noise suppression
- Red square: + Medium-duration processing
- Cyan diamond: Baseline MFCC + CMN

Clean
Contributions of PNCC components: background music (WSJ)

- Background music (WSJ)
- Temporal masking
- Noise protection
- Medium-time/time/freq anal
- Baseline MFCC with CMN
- Temporal masking
- Noise suppression
- Medium-duration processing
- Baseline MFCC + CMN

Accuracy (100 – WER) vs. SNR (dB)
Contributions of PNCC components: reverberation (WSJ)

- Reverberation (WSJ)
- Temporal masking
- Noise protection
- Medium-time frequency analysis

Baseline MFCC with CMN
- Temporal masking
- Noise suppression
- Medium-duration processing
- Baseline MFCC + CMN
PNCC and SSF @Google

The graph illustrates the accuracy (100 - WER) as a function of the reverberation time $T_{60}$ (ms). The graph compares the performance of SSF with power normalization and the baseline with power normalization. The accuracy decreases as the reverberation time increases.
Knowledge of the auditory system will improve ASR accuracy. Important aspects include:

- Consideration of filter shapes
- Consideration of rate-intensity function
- Onset enhancement
- Nonlinear modulation filtering
- Temporal suppression
General summary: Robust recognition in the 21st century

- Low SNRs, reverberated speech, speech maskers, and music maskers are difficult challenges for robust speech recognition.
- Robustness algorithms based on classical statistical estimation fail in the presence of transient degradation.
- Some more recent techniques that can be effective:
  - Missing-feature reconstruction
  - Microphone array processing in several forms
  - Processing motivated by monaural and binaural physiology and perception
- More information about this work may be found at http://www.cs.cmu.edu/~robust