Environmental robustness

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Automatic Speech Recognition— ASR Lecture 15
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Overview

Today's lecture

- Recognising speech in presence of additive noise
- Feature compensation approaches
- Model compensation approaches

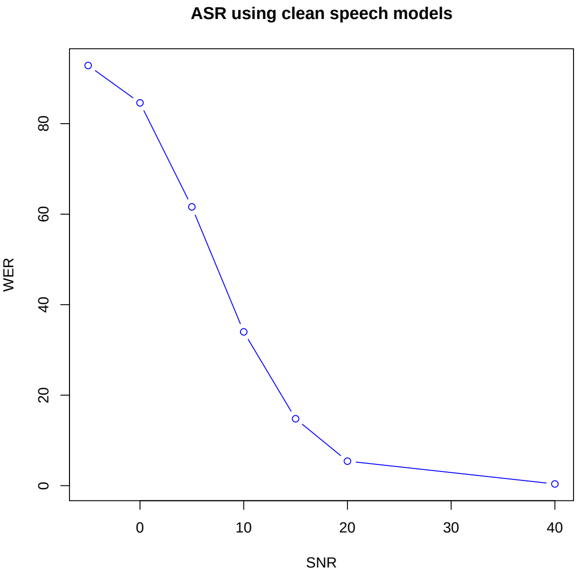
Additive Noise

- Multiple acoustic sources are the norm rather than the exception
- From the point of view of trying to recognize a single stream of speech, this is additive noise
- Stationary noise: frequency spectrum does not change over time (e.g. air conditioning, car noise at constant speed)
- Non-stationary noise: time-dependent frequency spectrum (e.g. breaking glass, workshop noise, music, speech)
- Measure the noise level as SNR (signal-to-noise ratio), measured in dB
  - 30dB SNR sounds noise free
  - 0dB SNR has equal signal and noise energy

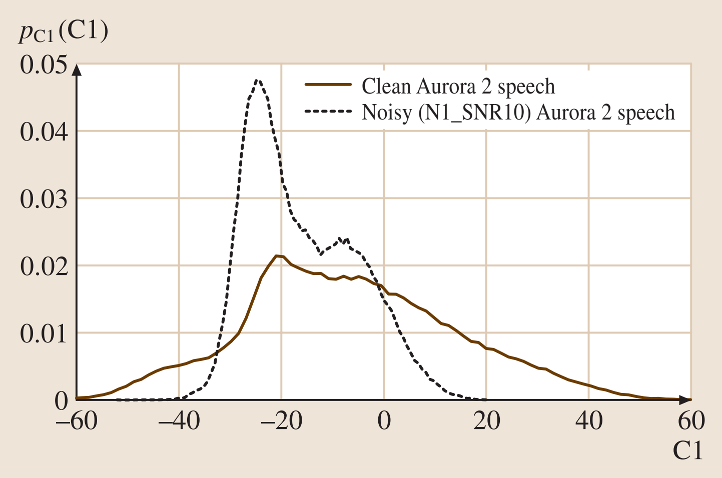
Aurora-2

- Aurora is a standard set of speech + noise databases used in robust ASR research
- Aurora-2 speaker-independent continuously spoken strings of digits (TI-digits)
    - 11 word vocabulary
    - Artificially added noise of different types:
        - A: subway, babble, car exhibition
        - B: restaurant, street, airport, station
        - C: subway, street

Recognizing Aurora-2 using Clean Speech Models



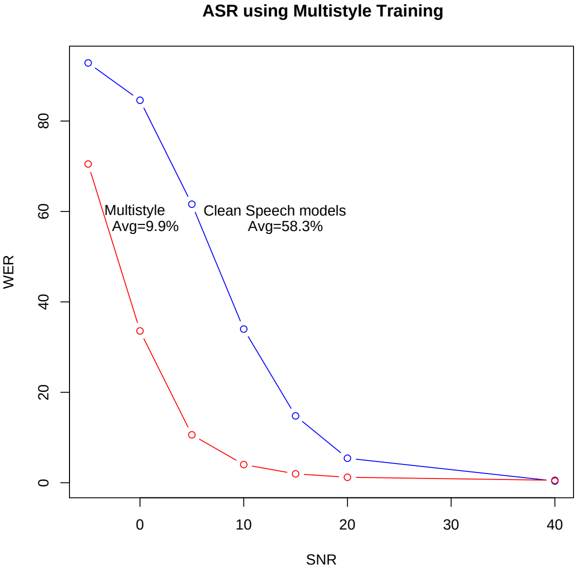
Mismatch between clean and noisy speech



Multistyle Training

- Basic idea: Don't train on clean speech, but train on speech with a similar noise level (and noise type)
- *Matched condition* — training in the same noise conditions as testing — is rarely possible since the test conditions are nearly always partly unknown
- *Multi-style training* — train with speech data in a variety of noise conditions
- It is possible to artificially mix recorded noise with clean speech at any desired SNR to create a multi-style training set
- Advantage: training data much better matched to test conditions
- Disadvantage: acoustic model components become less discriminative and less well matched to the training data
- Model adaptation — can further reduce errors using an adaptation technique such as MLLR

Recognizing Aurora-2 using Multistyle Training



Feature normalization

- Basic idea: Transform the features to reduce mismatch between training and test
- *Cepstral Mean Normalization* (CMN): subtract the mean of the feature vectors from each feature vector, so each feature vector element has a mean of 0
- CMN makes features robust to some linear filtering of the signal — adds robustness to varying microphones, telephone channels, etc.
- *Cepstral Variance Normalization* (CVN): Divide feature vector by standard deviation of feature vectors, so each feature vector element has a variance of 1
- Cepstral mean and variance normalisation, CMN/CVN:

$$\hat{\mathbf{x}}_i = \frac{\mathbf{x}_i - \boldsymbol{\mu}(\mathbf{x})}{\boldsymbol{\sigma}(\mathbf{x})}$$

On Aurora-2 CMN/CVN reduces multistyle training WER from 9.9% to 7.0%

Feature compensation: Spectral subtraction

- Basic idea: Estimate the noise spectrum and subtract it from the observed spectra
- Any feature vector can then be computed from the noise-subtracted spectrum
- Problems:
  - Need to estimate noise spectrum from a period of non-speech: requires good speech/non-speech detection
  - Errors in the noise estimate (perhaps arising from speech/non-speech separation errors) result in over-/under-compensation of the spectrum
- Low computational cost, widely used in practice
- "ETSI adavanced front end" uses spectral subtraction and CMN
  - 11.4% WER on Aurora-2 (clean models)
  - 6.8% WER on Aurora-2 (multistyle training)

Feature compensation: SPLICE

- Basic idea: Predict the observed clean speech **x** from the observed noisy speech **y**
- Estimate a joint mixture model for noisy and clean speech:

$$p(\mathbf{y}, \mathbf{x}) = \sum_k p(\mathbf{x}|\mathbf{y}, k) p(\mathbf{y}, k)$$

- $p(\mathbf{x}|\mathbf{y}, k)$ is a Gaussian component to predict the clean speech from the noisy speech:

$$p(\mathbf{x}|\mathbf{y}, k) = N(\mathbf{x}; A\mathbf{y} + \mathbf{b}, \mathbf{\Sigma}_{xy})$$

- $p(y, k)$ is itself a Gaussian component

$$p(\mathbf{y}, k) = N(\mathbf{y}; \boldsymbol{\mu}_k, \mathbf{\Sigma}_k) P(k)$$

- Train parameters from *stereo data*: simultaneous clean and noisy recordings
- Can use maximum likelihood or minimum mean square error objective function

Model-based compensation

- Basic idea: use the detailed acoustic models in the recognizer as the basis of the compensation scheme
- Feature compensation approaches use an additional (simple) model of the speech signal—at best, a GMM
- Model-based compensation: combine the clean-speech models with a noise model to result in a model of noisy speech
- Results in taking the product of clean speech and noise components: M clean speech components and noise components result in MN noisy speech components
- High computational complexity for noise models more complex than a single Gaussian
- Two important approaches
  - Parallel model compensation (PMC)
  - Vector Taylor series (VTS) approximation

Parallel model combination (PMC)

- Basic idea: Assume speech and noise is additive in spectral domain, so transform models from cepstral to spectral domain, compute noisy speech model statistics, transform back to cepstral domain
- Assume Gaussian noise model $N(\boldsymbol{\mu}_n, \boldsymbol{\Sigma}_n)$
- PMC, using log-normal approximation:
  1. Compute speech and noise models in cepstral domain
  2. Map to spectral domain using inverse of the DCT and exponential
  3. Combine speech and noise parameters in spectral domain

$$\boldsymbol{\mu}_y^f = \boldsymbol{\mu}_x^f + \boldsymbol{\mu}_n^f$$
$$\boldsymbol{\Sigma}_y^f = \boldsymbol{\Sigma}_x^f + \boldsymbol{\Sigma}_n^f$$

Even simpler approximation assumes $\boldsymbol{\Sigma}_\mathbf{y} = \boldsymbol{\Sigma}_\mathbf{x}$

Vector Taylor Series (VTS)

- Basic idea: Estimate noisy speech statistics as a Taylor series expansion about the means of the clean speech and noise
- Model the relationship between clean speech, noise and noisy speech as:

$$\mathbf{y} = \mathbf{x} + \mathbf{g}(\mathbf{n} - \mathbf{x})$$

  $\mathbf{g}$ is a nonlinear function mapping signal to noise ratio to the difference between clean and noisy speech

- Approximate using a first-order Taylor series expansion around the clean speech and noise means ($\boldsymbol{\mu}_x$, $\boldsymbol{\mu}_n$)

$$\mathbf{y} = \boldsymbol{\mu}_x + \mathbf{g}(\boldsymbol{\mu}_n - \boldsymbol{\mu}_x) + \frac{\partial \mathbf{y}}{\partial \mathbf{x}}(\mathbf{x} - \boldsymbol{\mu}_x) + \frac{\partial \mathbf{y}}{\partial \mathbf{n}}(\mathbf{n} - \boldsymbol{\mu}_n)$$

- This results in expressions for $\boldsymbol{\mu}_y$ and $\boldsymbol{\Sigma}_y$ based on the statistics (mean and covariance) of clean speech and noise models
- VTS, CMN/CVN and multistyle training results in state of the art Aurora-2 results: 6.2% WER

Missing feature approaches

- Basic idea: Assume each point in time-frequency plane is either reliable or unreliable evidence for the speech signal, and use this reliability to compute likelihoods
- Inspired by auditory scene analysis: each time-frequency point is dominated by energy from just one source
- Form a noise mask for those parts dominated by noise, and treat these as "missing" data for the speech
- Adjust the likelihood computation to take account of missing information
- Finding the noise mask:
  - Use SNR estimates
  - Use perceptual criteria (harmonics, common onset, etc.)
  - Train a classifier

Summary

- Feature compensation: cepstral mean/variance normalisation, spectral subtraction, SPLICE
- Model compensation: parallel model compensation, missing feature approaches
- Uncertainty decoding: use direct estimate of $p(\mathbf{y} \mid \mathbf{x})$ in model compensation