Speech Signal Analysis

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Automatic Speech Recognition— ASR Lectures 4&5
23 January 2019

Overview

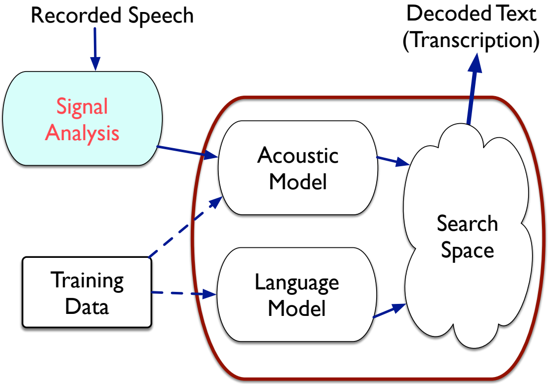
Speech Signal Analysis for ASR

- Features for ASR
- Spectral analysis
- Cepstral analysis
- Standard features for ASR: FBANK, MFCCs and PLP analysis
- Dynamic features

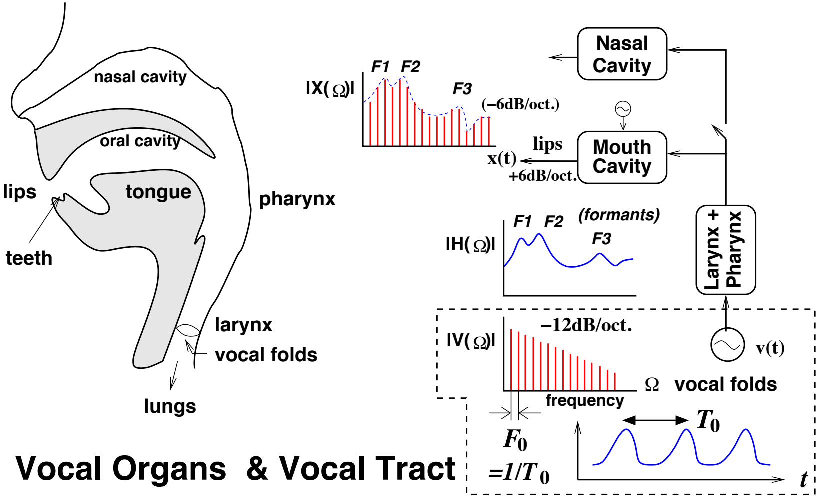
Reading:

- Jurafsky & Martin, sec 9.3
- P Taylor, *Text-to-Speech Synthesis*, chapter 12, signal processing background chapter 10

Speech signal analysis for ASR



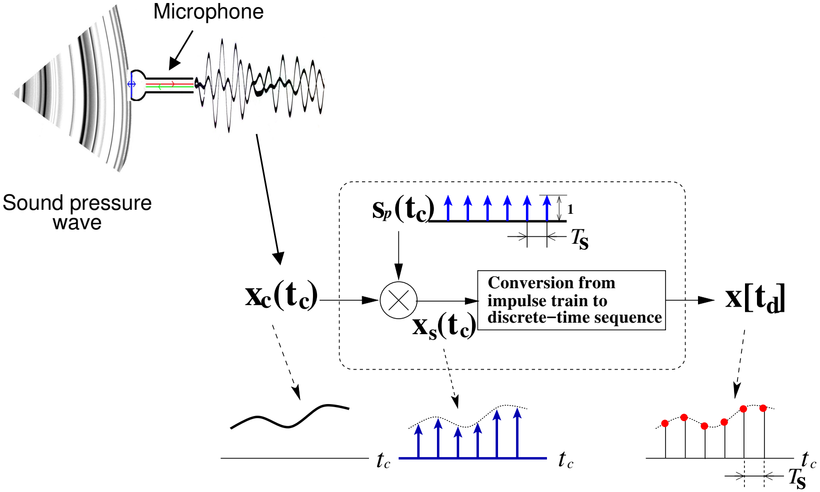
Speech production model



(F_0 : fundamental frequency)

A/D conversion — Sampling

Convert analogue signals in digital form



A/D conversion — Sampling *(cont.)*

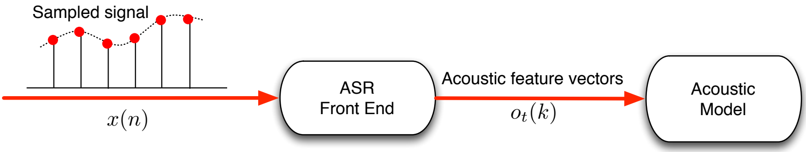
Things to know:

- Sampling Frequency ($F_s = 1/T_s$)

Speech	Sufficient F_s
Microphone voice ($< 10kHz$)	20 kHz
Telephone voice ($< 4kHz$)	8 kHz

- Analogue low-pass filtering to avoid 'aliasing'
  NB: the cut-off frequency should be less than the Nyquist frequency ($= F_s/2$)

Acoustic Features for ASR



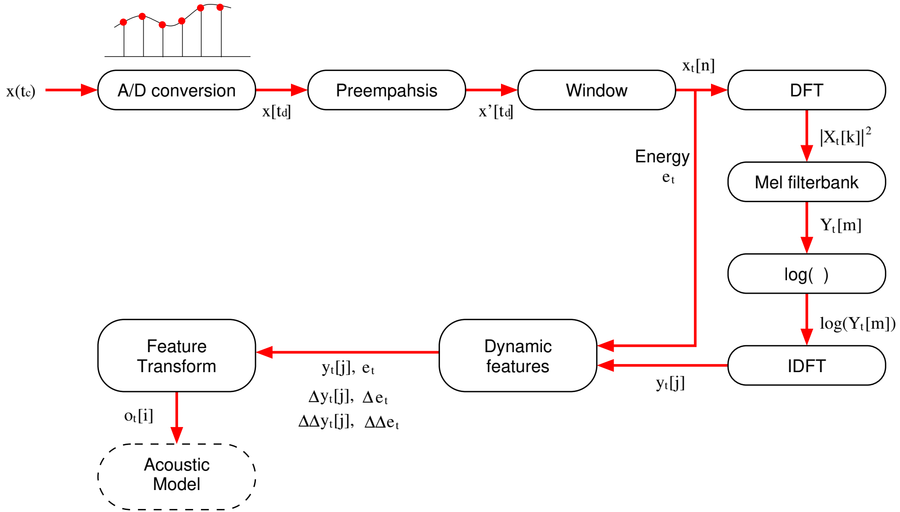
Speech signal analysis to produce a sequence of acoustic feature vectors

Acoustic Features for ASR

Desirable characteristics of acoustic features used for ASR:

- Features should contain sufficient information to distinguish between phones
  - good time resolution (10ms)
  - good frequency resolution (20 $\sim$ 40 channels)
- Be separated from F_0 and its harmonics
- Be robust against speaker variation
- Be robust against noise or channel distortions
- Have good "pattern recognition characteristics"
  - low feature dimension
  - features are independent of each other (NB: this applies to GMMs, but not required for NN-based systems)

MFCC-based front end for ASR

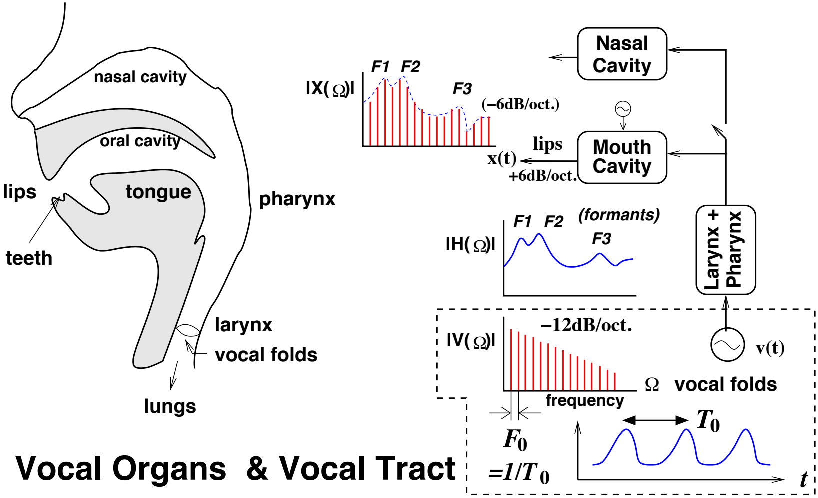


Pre-emphasis and spectral tilt

- Pre-emphasis increases the magnitude of higher frequencies in the speech signal compared with lower frequencies
- *Spectral Tilt*
  - The speech signal has more energy at low frequencies (for voiced speech)
  - This is due to the glottal source (see the figure)
- Pre-emphasis (first-order) filter boosts higher frequencies:

$$x'[t_d] = x[t_d] - \alpha x[t_d - 1] \qquad 0.95 < \alpha < 0.99$$

Speech production model



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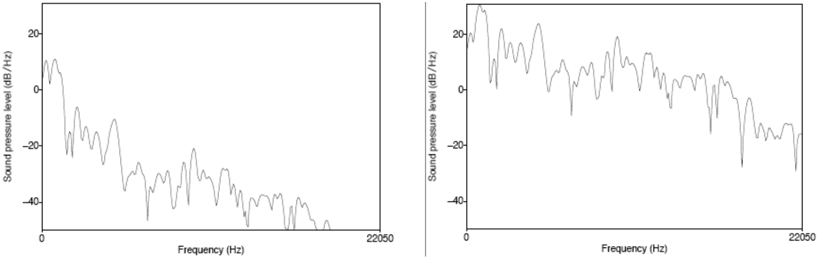
Pre-emphasis: example



Vowel /aa/ - time slice of the spectrum

(Jurafsky & Martin, fig. 9.9)

Windowing

- The speech signal is constantly changing (non-stationary)
- Signal processing algorithms usually assume that the signal is stationary
- Piecewise stationarity: model speech signal as a sequence of **frames** (each assumed to be stationary)
- **Windowing**: multiply the full waveform $s[n]$ by a window $w[n]$ (in time domain):

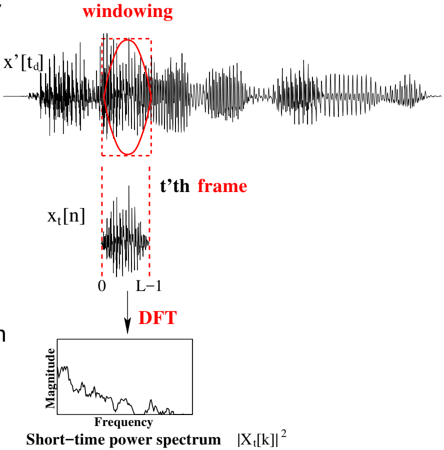
$$x[n] = w[n]\, s[n] \qquad (\ x_t[n] = w[n]\, x'[t_d + n]\ )$$

- Simply cutting out a short segment (frame) from $s[n]$ is a rectangular window — causes discontinuities at the edges of the segment
- Instead, a tapered window is usually used
  e.g. *Hamming* ($\alpha = 0.46164$) or *Hanning* ($\alpha = 0.5$) window

$$w[n] = (1-\alpha) - \alpha \cos\left(\frac{2\pi n}{L-1}\right) \qquad L:\ \text{window width}$$

Windowing and spectral analysis

- *Window* the signal $x'[t_d]$ into frames $x_t[n]$ and apply Fourier Transform to each segment.
  - Short frame width: *wide-band*, high time resolution, low frequency resolution
  - Long frame width: *narrow-band*, low time resolution, high frequency resolution
- For ASR:
  - frame width $\sim 25ms$
  - frame shift $\sim 10ms$



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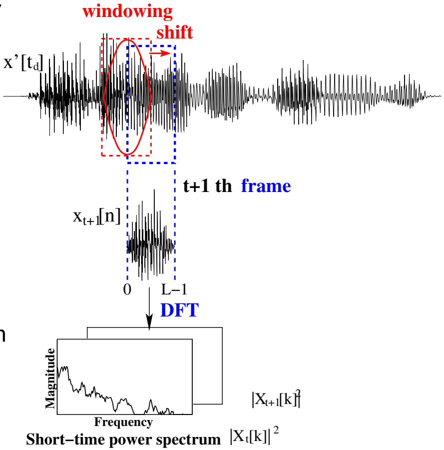
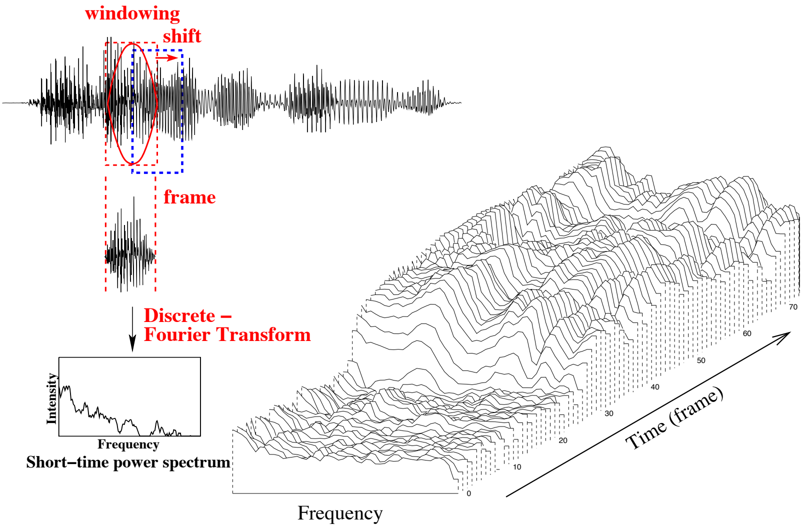


Short-time spectral analysis



Discrete Fourier Transform (DFT)

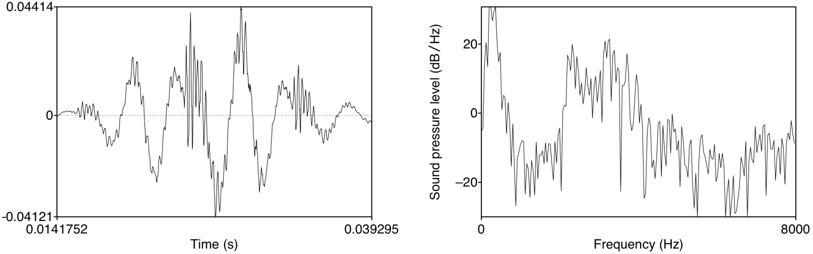
- Purpose: extracts spectral information from a windowed signal (i.e. how much energy at each frequency band)
- Input: windowed signal $x[0], \ldots, x[L-1]$ (time domain)
- Output: a complex number $X[k]$ for each of N frequency bands representing magnitude and phase for the kth frequency component (frequency domain)
- Discrete Fourier Transform (DFT):

$$X[k] = \sum_{n=0}^{N-1} x[n] \exp\left(-j\frac{2\pi}{N}kn\right)$$

NB: $\exp(j\theta) = e^{j\theta} = \cos(\theta) + j\sin(\theta)$

- Fast Fourier Transform (FFT) — efficient algorithm for computing DFT when N is a power of 2, and $N \geq L$.

DFT Spectrum



25ms Hamming window of vowel /iy/ and its spectrum computed by DFT

(Jurafsky and Martin, fig 9.12)

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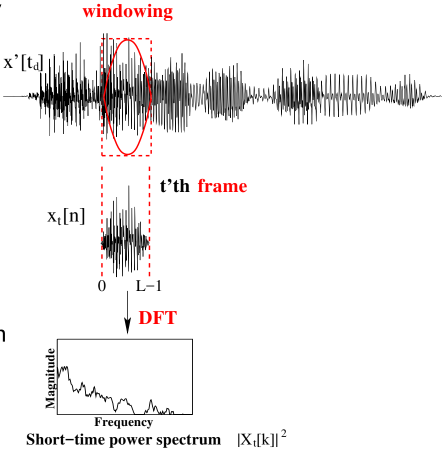

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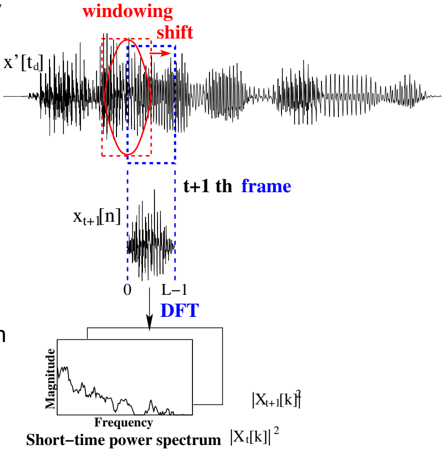

Wide-band and narrow-band spectrograms

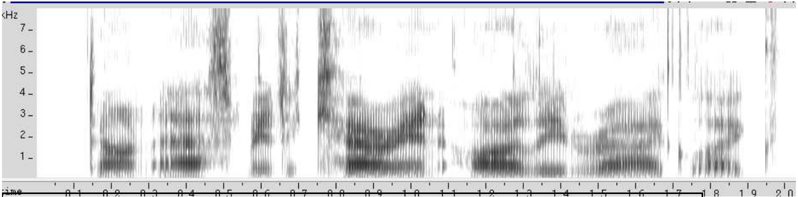

Figure 12.8 Wide band spectrogram window width = 2.5ms

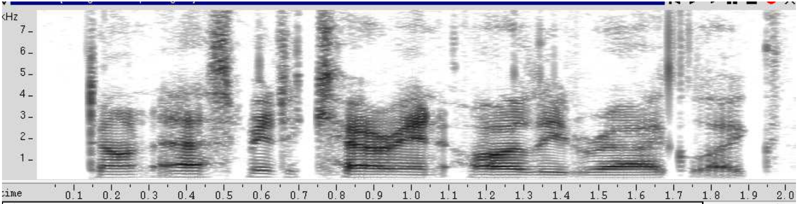

Figure 12.9 Narrow band spectrogram window width = 25ms

(Taylor, figs 12.8, 12.9)

Windowing and spectral analysis

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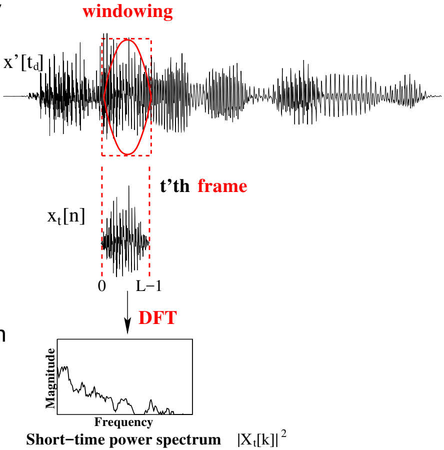

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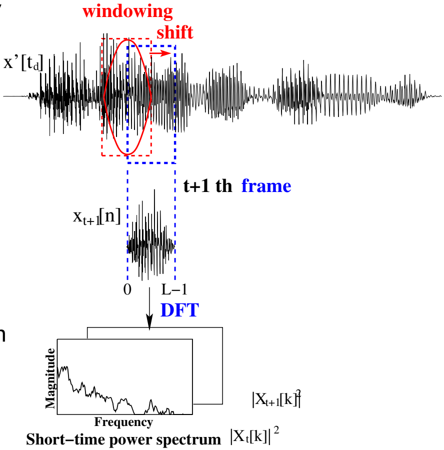
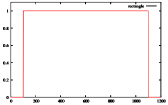
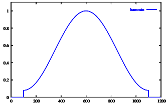


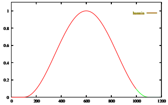
Effect of windowing — time domain



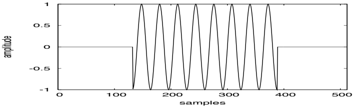
Rectangular



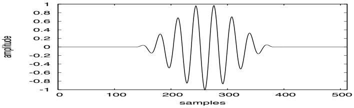
Hamming



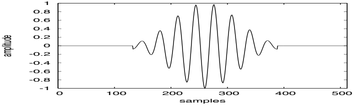
Hanning



(a) Rectangular window



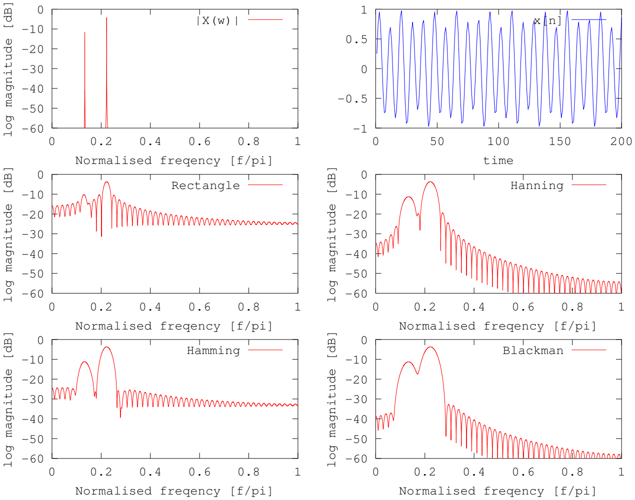
(b) Hanning window



(c) Hamming window

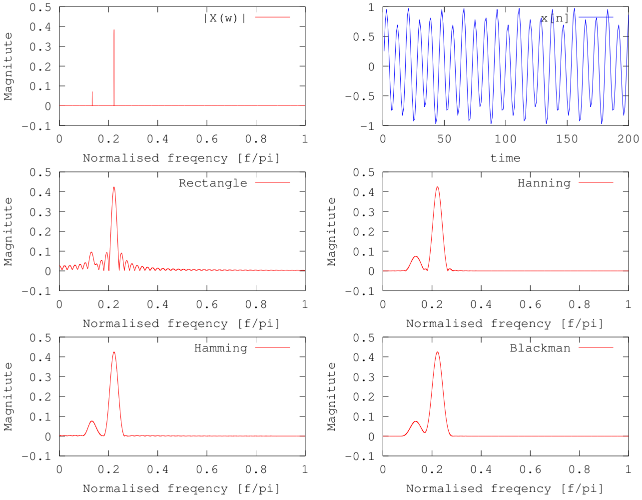
(Taylor, fig 12.1)

Effect of windowing — frequency domain



$$x(t) = 0.15 \sin(2\pi f_1 t) + 0.85 \sin(2\pi f_2 t + 0.3)$$
$$f_1 = 0.13, \;\; f_2 = 0.22$$

Effect of windowing — frequency domain



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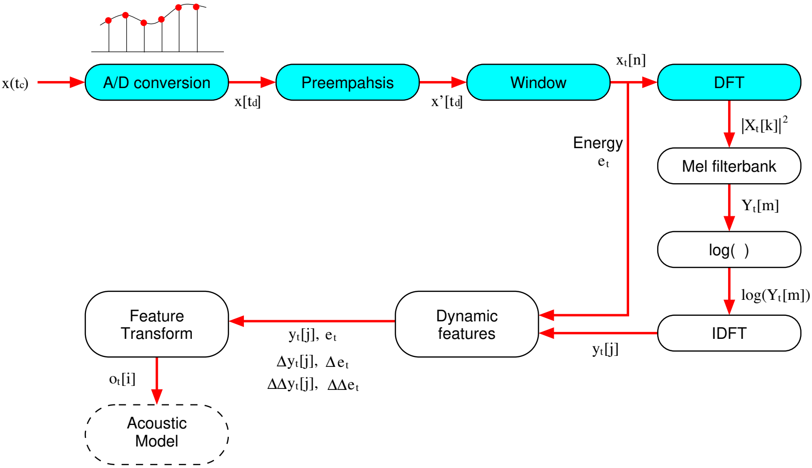
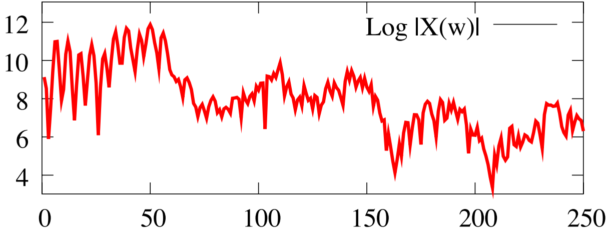
MFCC-based front end for ASR



DFT Spectrum Features for ASR

- Equally-spaced frequency bands — but human hearing less sensitive at higher frequencies (above $\sim$ 1000Hz)
- The estimated power spectrum contains harmonics of F0, which makes it difficult to estimate the envelope of the spectrum



- Frequency bins of STFT are highly correlated each other, i.e. power spectrum representation is highly redundant

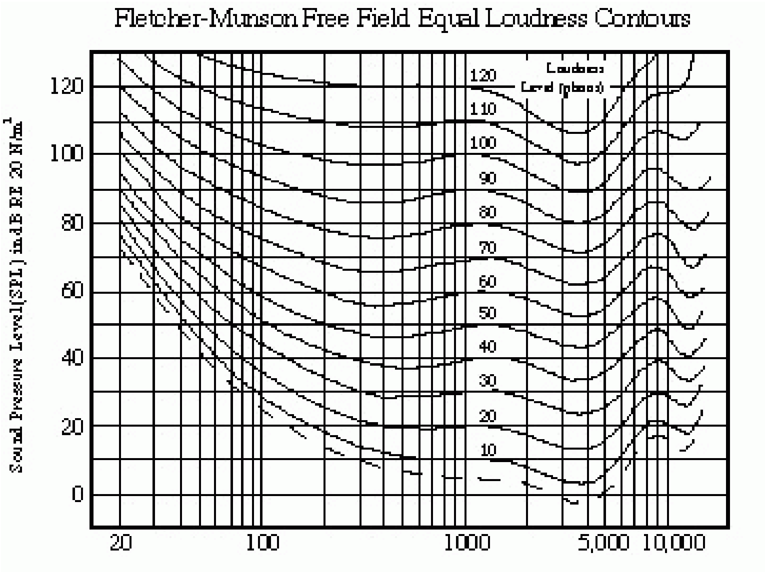
Human hearing

Physical quality	Perceptual quality
Intensity	Loudness
Fundamental frequency	Pitch
Spectral shape	Timbre
Onset/offset time	Timing
Phase difference in binaural hearing	Location

Technical terms

- equal-loudness contours
- masking
- auditory filters (critical-band filters)
- critical bandwidth

Equal loudness contour

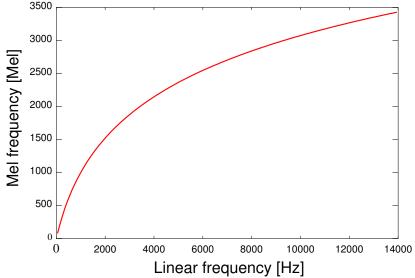


Nonlinear frequency scaling

Human hearing is less sensitive to higher frequencies — thus human perception of frequency is nonlinear

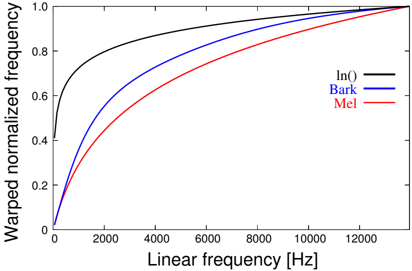
Mel scale

$$M(f) = 1127 \ln(1 + f/700)$$



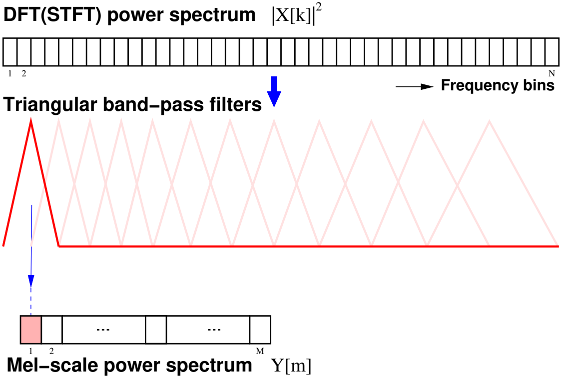
Bark scale

$$b(f) = 13 \arctan(0.00076 f) + 3.5 \arctan((f/7500)^2)$$



Mel-Filter Bank

- Apply a mel-scale filter bank to DFT power spectrum to obtain mel-scale power spectrum
- Each filter collects energy from a number of frequency bands in the DFT
- Linearly spaced < 1000 Hz, logarithmically spaced > 1000 Hz



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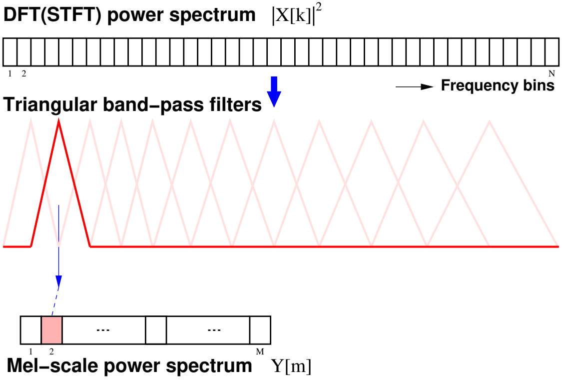

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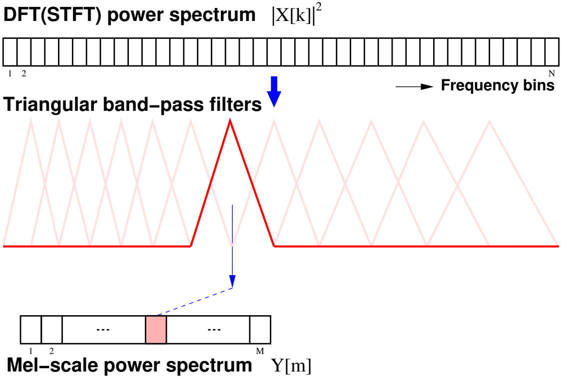

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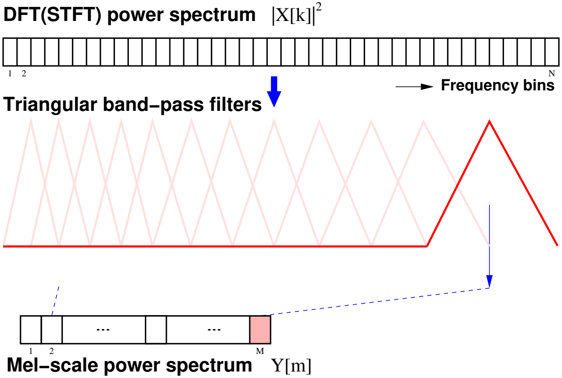

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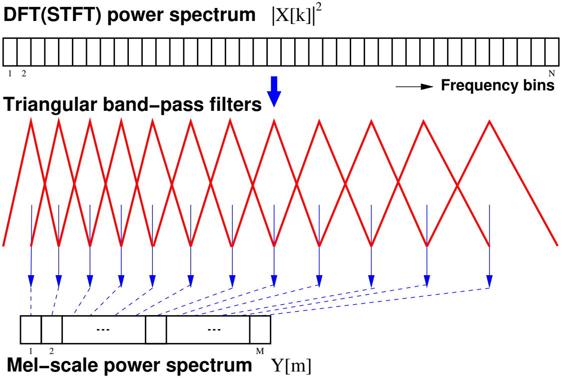


Mel-Filter Bank *(cont.)*

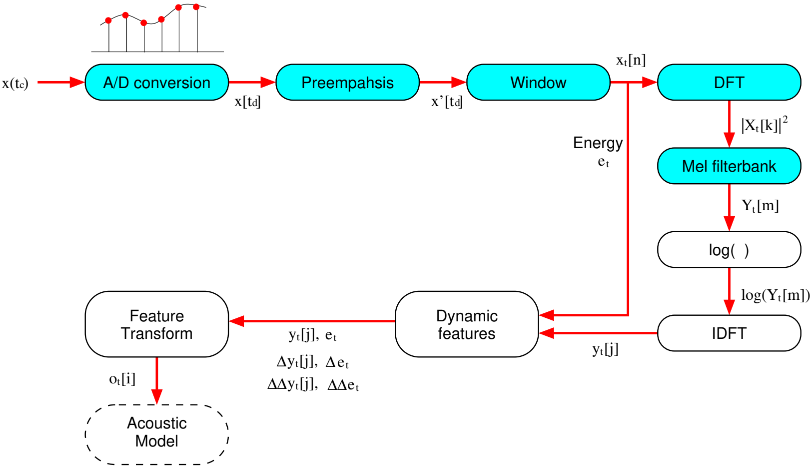
$$Y_t[m] = \sum_{k=1}^{N} W_m[k] \, |X_t[k]|^2$$

where k : DFT bin number $(1, \ldots, N)$
m : mel-filter bank number $(1, \ldots, M)$.

- How many number of mel-filter channels?

≈ 20 for GMM-HMM based ASR
$20 \sim 40$ for DNN (+HMM) based ASR

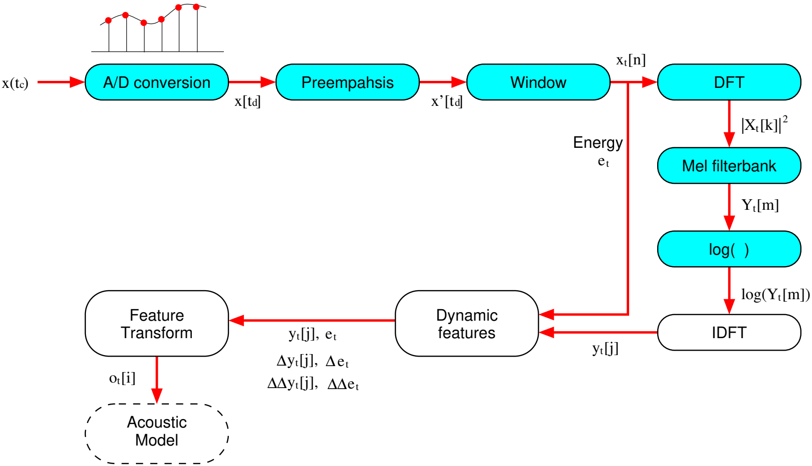
MFCC-based front end for ASR



Log Mel Power Spectrum

- Compute the log magnitude squared of each mel-filter bank output: $\log Y[m]$
  - Taking the log compresses the dynamic range
  - Human sensitivity to signal energy is logarithmic — i.e. humans are less sensitive to small changes in energy at high energy than small changes at low energy
  - Log makes features less variable to acoustic coupling variations
  - Removes phase information — not important for speech recognition (not everyone agrees with this)
- Aka "log mel-filter bank outputs" or "FBANK features", which are widely used in recent DNN-HMM based ASR systems

MFCC-based front end for ASR



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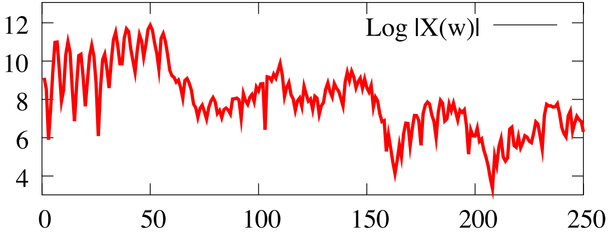
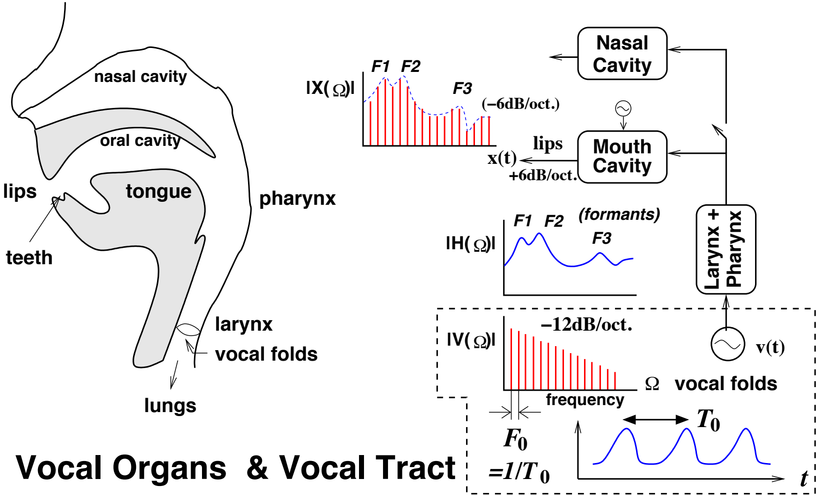


- Frequency bins of STFT are highly correlated each other, i.e. power spectrum representation is highly redundant

Cepstral Analysis

- Source-Filter model of speech production
  - **Source**: Vocal cord vibrations create a glottal source waveform
  - **Filter**: Source waveform is passed through the vocal tract: position of tongue, jaw, etc. give it a particular shape and hence a particular filtering characteristic
- Source characteristics (F_0, dynamics of glottal pulse) do not help to discriminate between phones
- The filter specifies the position of the articulators
- ... and hence is directly related to phone discrimination
- Cepstral analysis enables us to separate source and filter

Speech production model



(F_0 : fundamental frequency)

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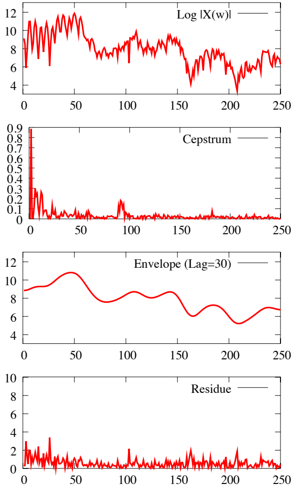
Cepstral Analysis

Split power spectrum into spectral envelope and F_0 harmonics.



Log spectrum (freq domain)

$\Downarrow$ Inverse Fourier Transform

Cepstrum (time domain) (*quefrency*)

$\Downarrow$ Liftering to get low/high part
(*lifter*: filter used in cepstral domain)

$\Downarrow$ Fourier Transform

Smoothed log spectrum (freq domain)
[low-part of cepstrum]

$+$

Fine structure
[high-part of cepstrum]

The Cepstrum

- Cepstrum obtained by applying inverse DFT to log magnitude spectrum (may be mel-scaled)
- Cepstrum is time-domain (we talk about quefrency)
- Inverse DFT:

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] \exp\left(j \frac{2\pi}{N} nk \right)$$

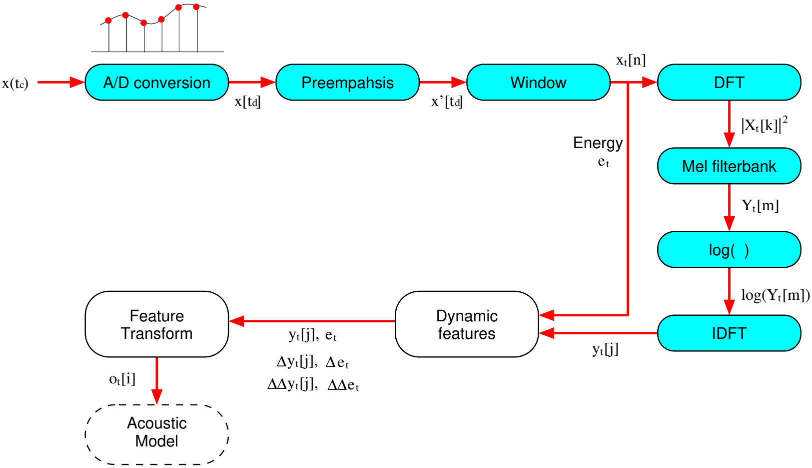
- Since log power spectrum is real and symmetric the inverse DFT is equivalent to a discrete cosine transform (DCT)

$$y_t[n] = \sum_{m=0}^{M-1} \log(Y_t[m]) \cos\left(n(m+0.5)\frac{\pi}{M} \right) \ , \quad n = 0, \ldots, J$$

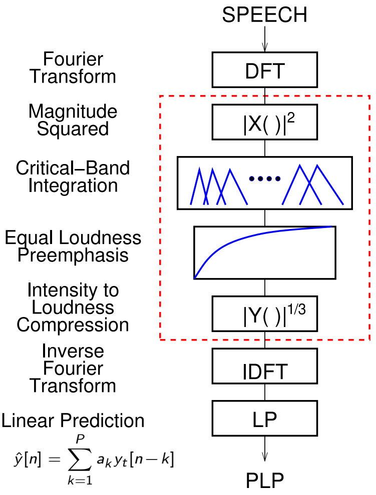
MFCCs

- Smoothed spectrum: transform to cepstral domain, truncate, transform back to spectral domain
- Mel-frequency cepstral coefficients (MFCCs): use the cepstral coefficients directly
  - Widely used as acoustic features in HMM-based ASR
  - First 12 MFCCs are often used as the feature vector (removes F0 information)
  - Less correlated than spectral features — easier to model than spectral features
  - Very compact representation — 12 features describe a 20ms frame of data
  - For standard HMM-based systems, MFCCs result in better ASR performance than filter bank or spectrogram features
  - MFCCs are not robust against noise

MFCC-based front end for ASR



PLP — Perceptual Linear Prediction



$$\hat{y}[n] = \sum_{k=1}^{P} a_k y_t[n-k]$$

- PLP (Hermansky, JASA 1990)
- Uses equal loudness pre-emphasis and cube-root compression (motivated by perceptual results) rather than log compression
- Uses linear predictive auto-regressive modelling to obtain cepstral coefficients
- PLP has been shown to lead to
  - slightly better ASR accuracy
  - slightly better noise robustness

  compared with MFCCs

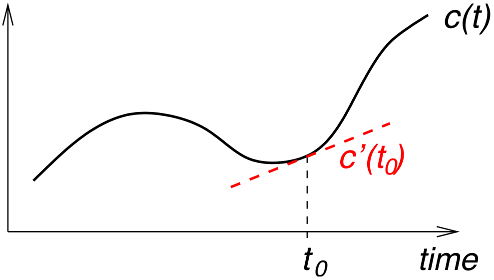
Dynamic features

- Speech is not constant frame-to-frame, so we can add features to do with how the cepstral coefficients change over time
- $\Delta *$, $\Delta^2 *$ are delta features (dynamic features / time derivatives)
- Simple calculation of delta features $d(t)$ at time t for cepstral feature $c(t)$ (e.g. $y_t[j]$):

$$d(t) = \frac{c(t+1) - c(t-1)}{2}$$

- More sophisticated approach estimates the temporal derivative by using regression to estimate the slope (typically using 4 frames each side)
- "Standard" ASR features (for GMM-based systems) are 39 dimensions:
    - 12 MFCCs, and energy
    - 12 ΔMFCCs, Δenergy
    - 12 Δ^2MFCCs, Δ^2energy

Estimating dynamic features



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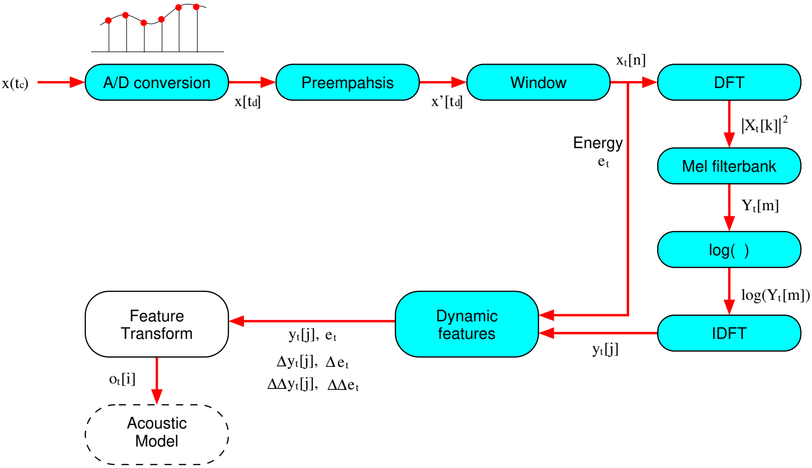

Feature Transforms

- Orthogonal transformation (orthogonal bases)
  - **DCT** (discrete cosine transform)
  - **PCA** (principal component analysis)
- Transformation based on the bases that maximises the separability between classes.
  - **LDA** (linear discriminant analysis) / Fisher's linear discriminant
  - **HLDA** (heteroscedastic linear discriminant analysis)

Feature Normalisation

- Basic Idea: Transform the features to reduce mismatch between training and test
- *Cepstral Mean Normalisation* (CMN): subtract the average feature value from each feature, so each feature has a mean value of 0. makes features robust to some linear filtering of the signal (channel variation)
- *Cepstral Variance Normalisation* (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:

$$\hat{y}_t[j] = \frac{y_t[j] - \mu(y[j])}{\sigma(y[j])}$$

- Compute mean and variance statistics over longest available segments with the same speaker/channel
- Real time normalisation: compute a moving average

Acoustic features in state-of-the-art ASR systems

See Tables 1, 2, and 3 in

Jinyu Li, Dong Yu, Jui-Ting Huang, and Yifan Gong,
"Improving Wideband Speech Recognition Using Mixed-Bandwidth Training Data In CD-DNN-HMM",
2012 IEEE Workshop in Spoken Language Technology (SLT2012).
https://doi.org/10.1109/SLT.2012.6424210

Table 1: Comparison of different input features for DNN. All the input features are mean-normalized and with dynamic features. Relative WER reduction in parentheses.

Setup	**WER (%)**
CD-GMM-HMM (MFCC, fMPE+BMMI)	34.66 (**baseline**)
CD-DNN-HMM (MFCC)	31.63 (-8.7%)
CD-DNN-HMM (24 log filter-banks)	30.11 (-13.1%)
CD-DNN-HMM (29 log filter-banks)	30.11 (-13.1%)
CD-DNN-HMM (40 log filter-banks)	29.86 (-13.8%)
CD-DNN-HMM (256 log FFT bins)	32.26 (-6.9%)

Table 2: Comparison of DNNs with and without dynamic features. All the input features are mean normalized.

CD-DNN-HMM (40 log filter-banks)	**WER (%)**
static+Δ+$\Delta\Delta$ (11-frame)	29.86
static only (11-frame)	31.11
static only (19-frame)	30.48

Table 3: Comparison of features with and without mean normalization. Dynamic features are used.

CD-DNN-HMM (29 log filter banks)	**WER (%)**
With mean normalization	30.11
Without mean normalization	29.96

Summary: Speech Signal Analysis for ASR

- Good characteristics of ASR features
- FBANK features
  - Short-time DFT analysis
  - Mel-filter bank
  - Log magnitude squared
  - Widely used for DNN ASR ($M \approx 40$)
- MFCCs - mel frequency cepstral coefficients
  - FBANK features
  - Inverse DFT (DCT)
  - Use first few (12) coefficients
  - Widely used for GMM-HMM ASR
- Delta features (dynamic features)
- 39-dimension feature vector (for GMM-HMM ASR): MFCC-12 + energy; + Deltas; + Delta-Deltas

References

- J&M: Daniel Jurafsky and James H. Martin (2008). Speech and Language Processing, Pearson Education (2nd edition).
- Taylor: Paul Taylor (2009). Text-to-Speech Synthesis, Cambridge University Press.
- Hynek Hermansky, "Perceptual linear predictive (PLP) analysis of speech," The Journal of the Acoustical Society of America, Vol.87, No.4, pp.1737–1752, 1980.