# Speech Signal Analysis

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Automatic Speech Recognition— ASR Lectures 2&3
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# Overview

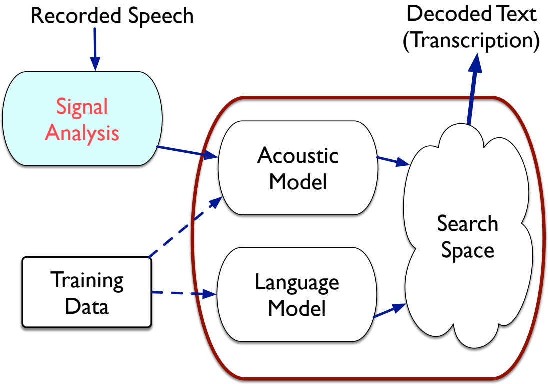
## Speech Signal Analysis for ASR

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

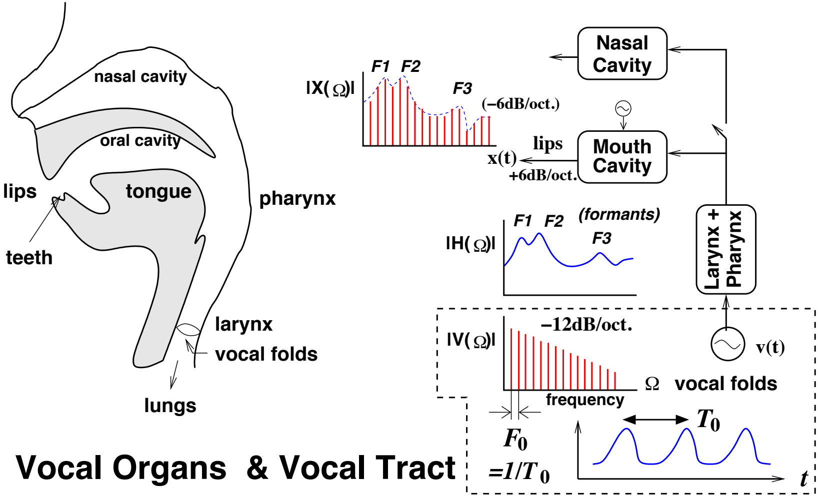
Reading:

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

# Speech signal analysis for ASR



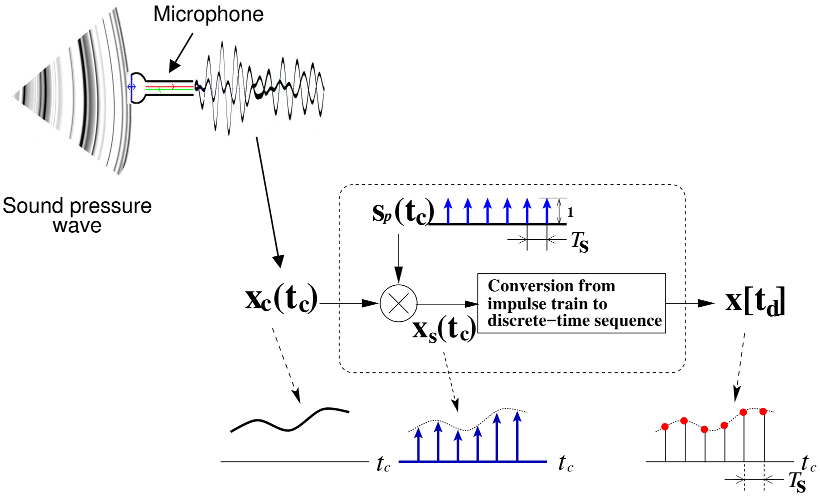
# Speech production model




($F_0$ : fundamental frequency)

# A/D conversion — Sampling

Convert analogue signals in digital form



# A/D conversion — Sampling *(cont.)*

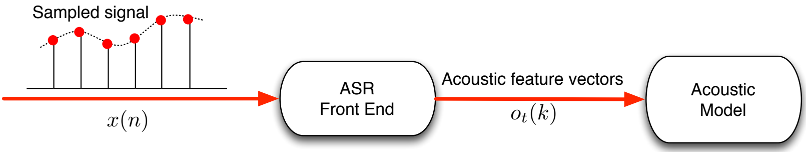
Things to know:

- 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



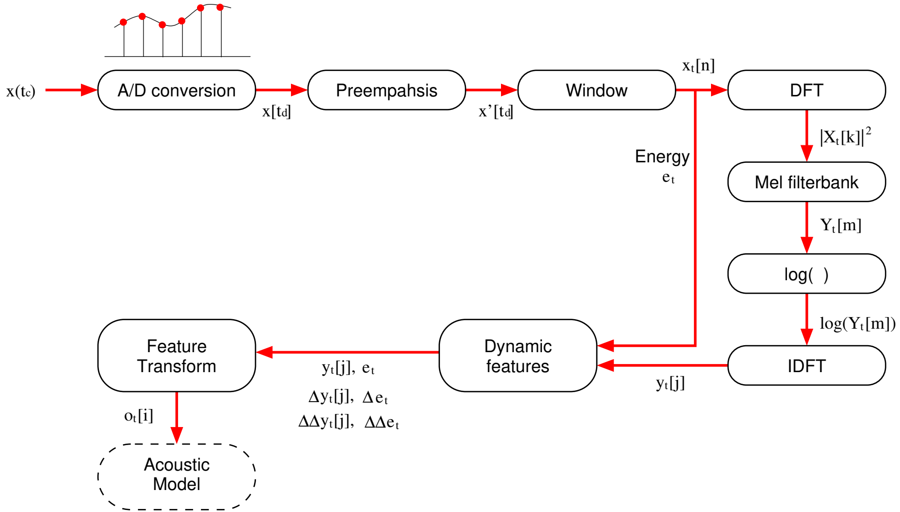

Speech signal analysis to produce a sequence of acoustic feature vectors

# 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

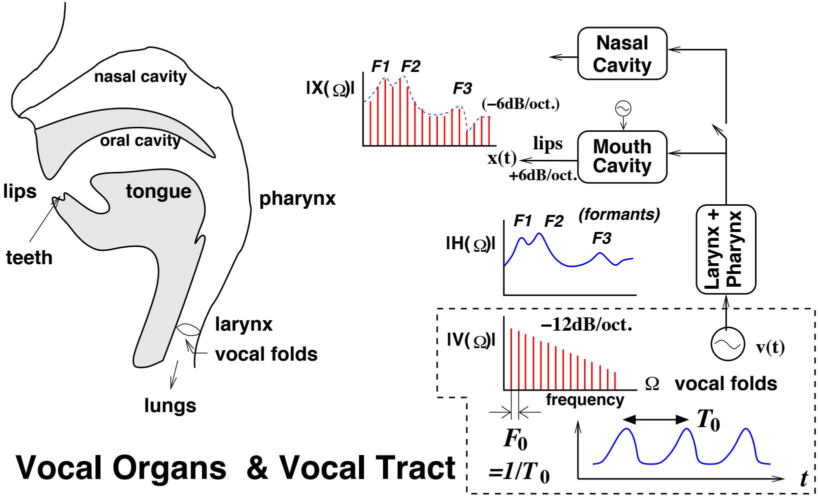


# Pre-emphasis and spectral tilt

- 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:

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

# Speech production model

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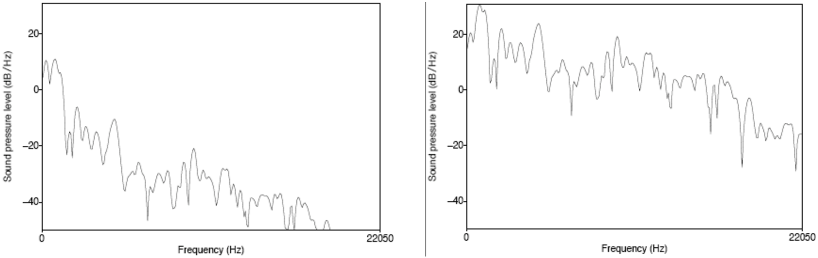
# Pre-emphasis: example




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):

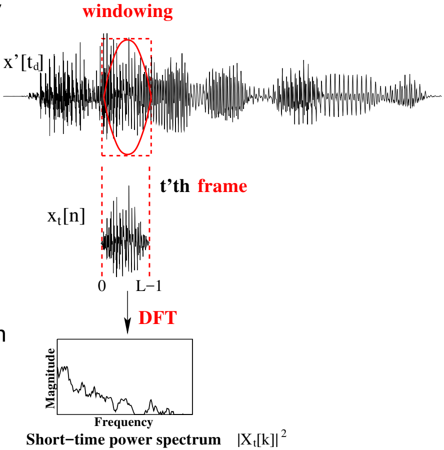
$$x[n] = w[n]\, s[n] \qquad (\ x_t[n] = w[n]\, x'[t_d + n]\ )$$

- 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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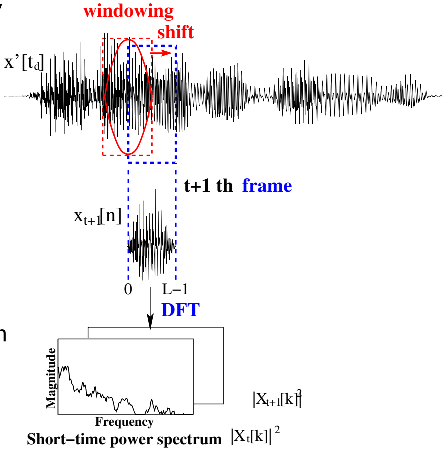
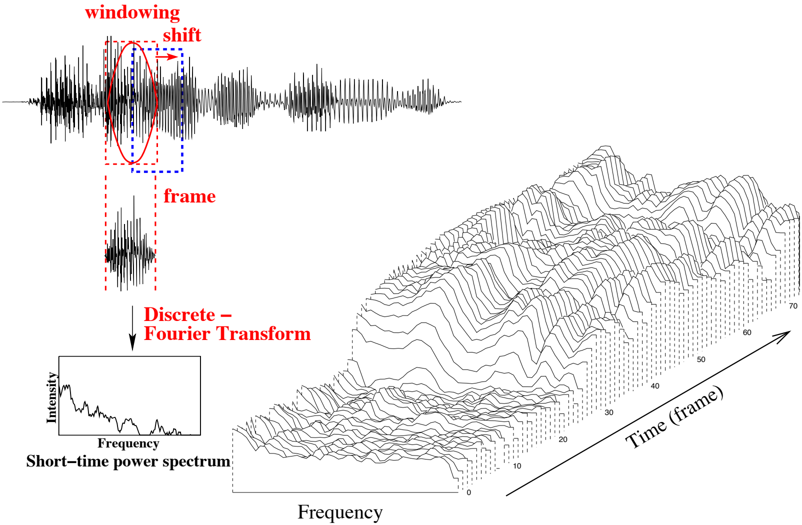


# Short-time spectral analysis



# Discrete Fourier Transform (DFT)

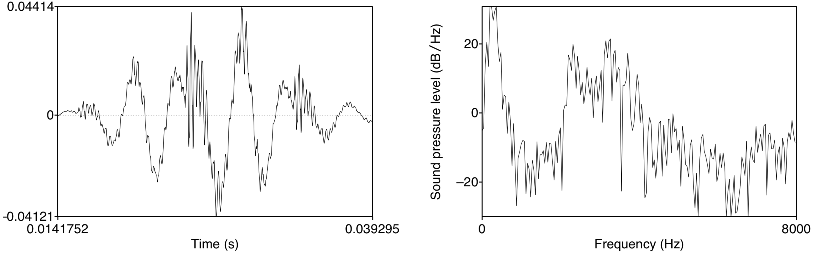
- Purpose: extracts spectral information from a windowed signal (i.e. how much energy at each frequency band)
- Input: windowed signal $x[0], \ldots, x[L-1]$ (time domain)
- Output: a complex number $X[k]$ for each of $N$ frequency bands representing magnitude and phase for the $k$th frequency component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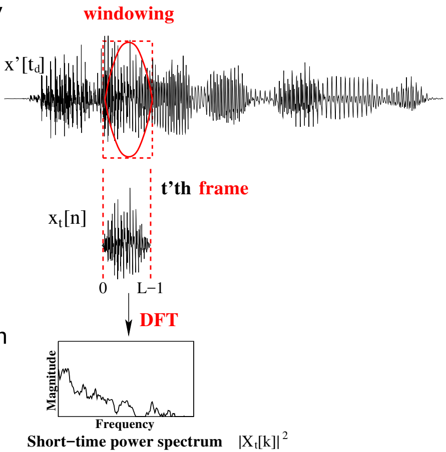

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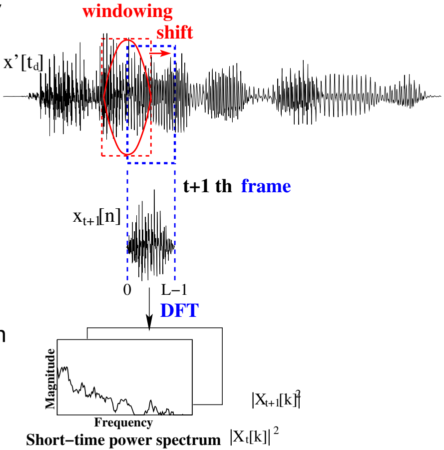

# Wide-band and narrow-band spectrograms

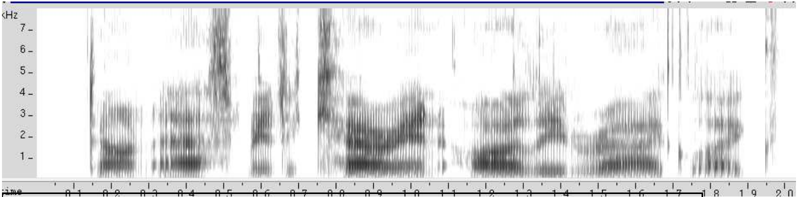


**Figure 12.8** Wide band spectrogram window width = 2.5ms

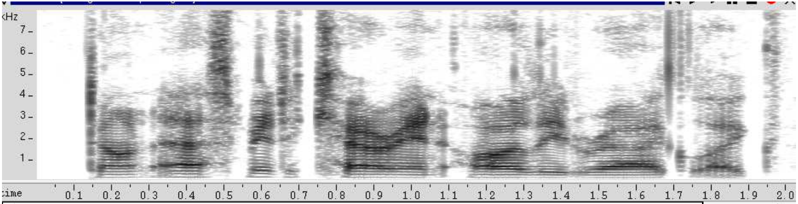


**Figure 12.9** Narrow band spectrogram window width = 25ms

(Taylor, figs 12.8, 12.9)

# Windowing and spectral analysis

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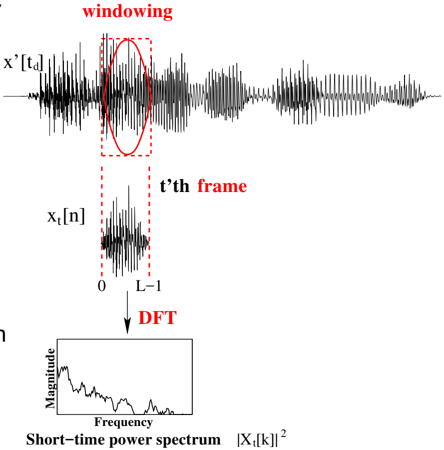

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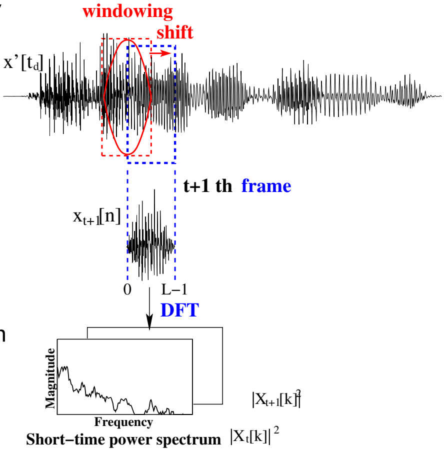
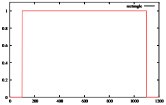
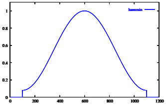


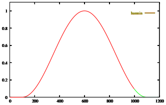
# Effect of windowing — time domain



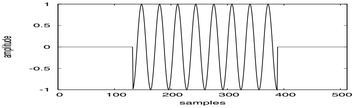
Rectangular



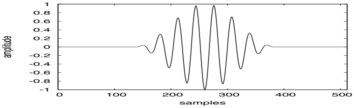
Hamming



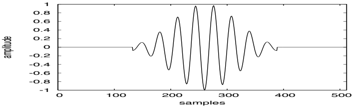
Hanning




(a) Rectangular window



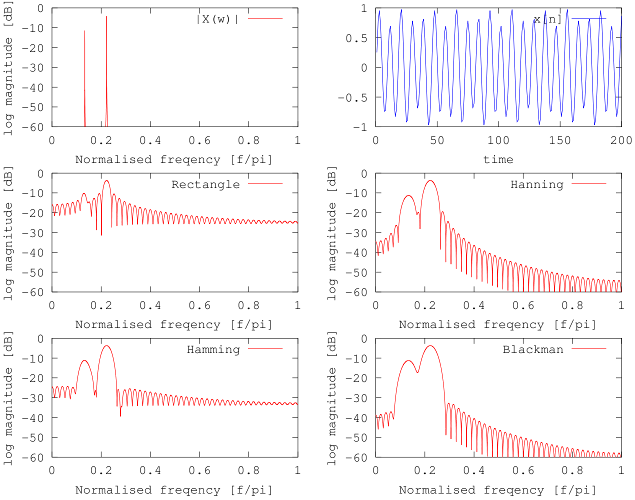

(b) Hanning window




(c) Hamming window

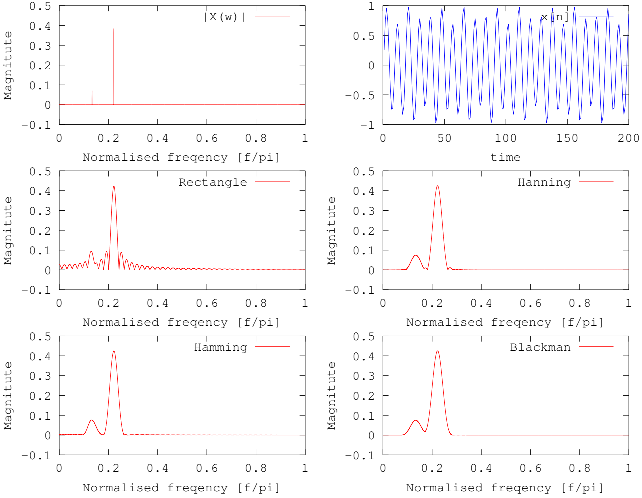
(Taylor, fig 12.1)

# 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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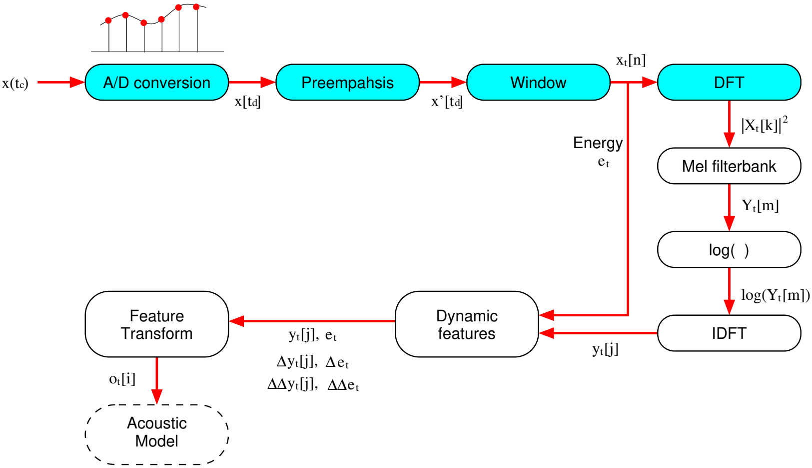
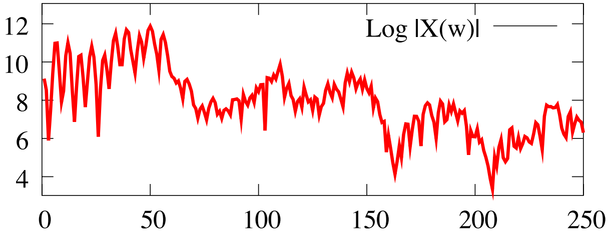
# MFCC-based front end for ASR



# 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

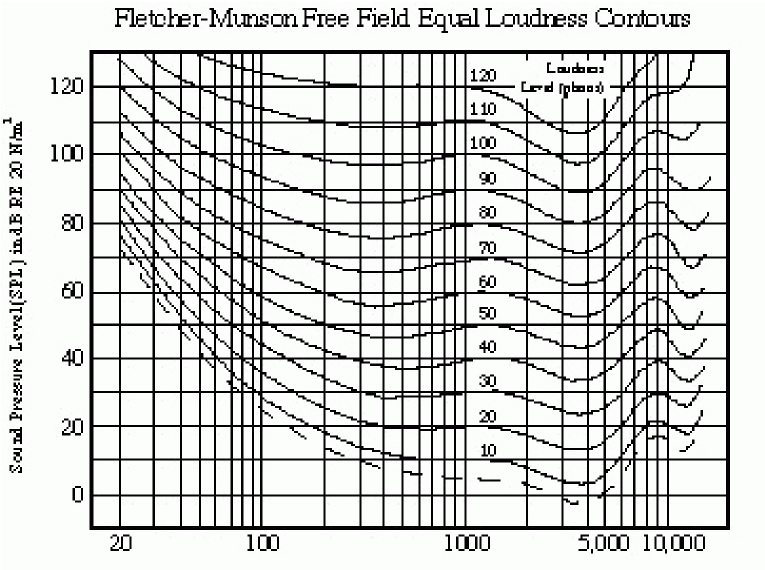
# Human hearing

| 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

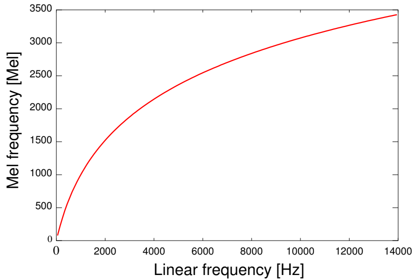


# Nonlinear frequency scaling

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

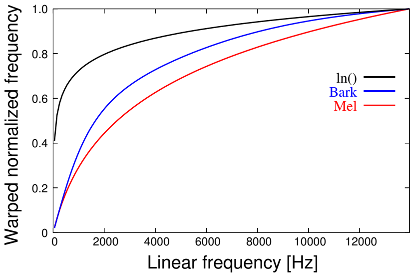
**Mel scale**

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



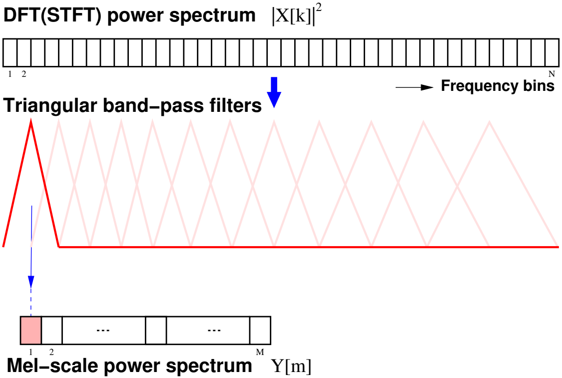

**Bark scale**

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



# 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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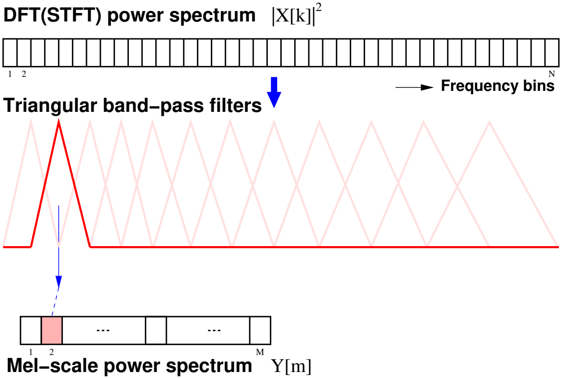

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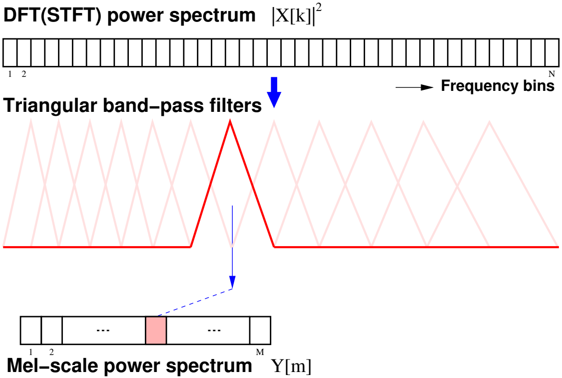

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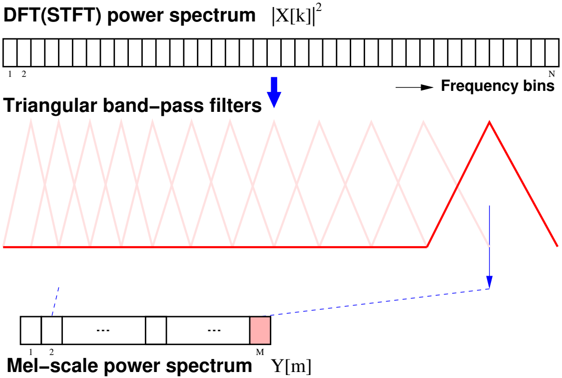

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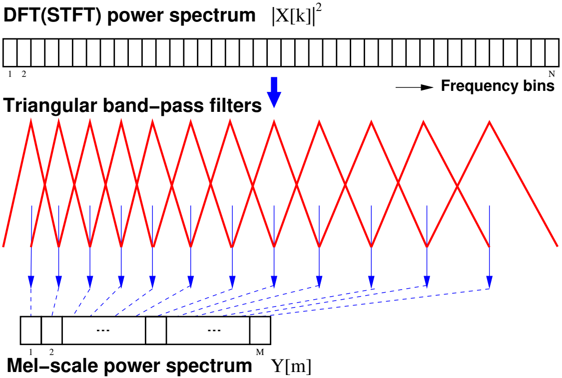


# Mel-Filter Bank *(cont.)*

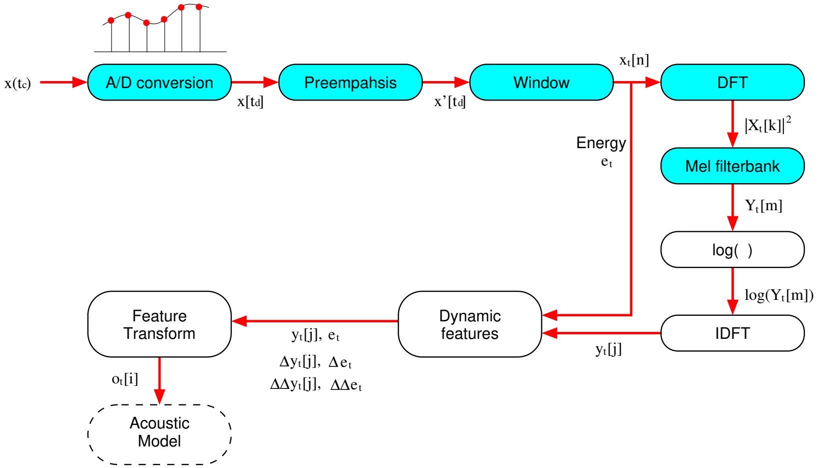
$$Y_t[m] = \sum_{k=1}^{N} W_m[k] \, |X_t[k]|^2$$

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

- How many number of mel-filter channels?

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

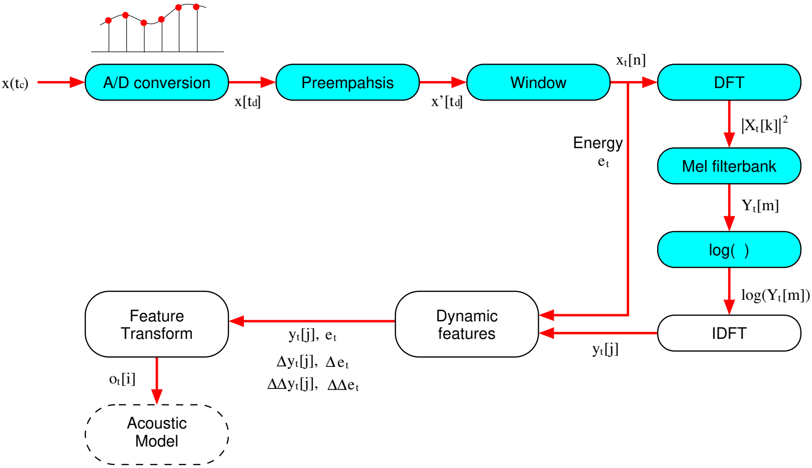
# MFCC-based front end for ASR



# 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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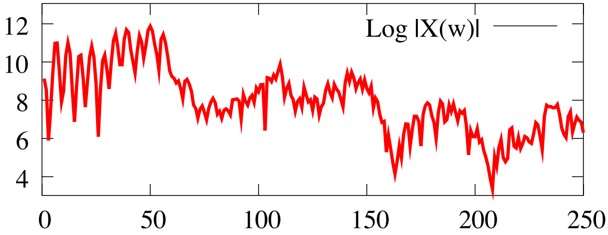
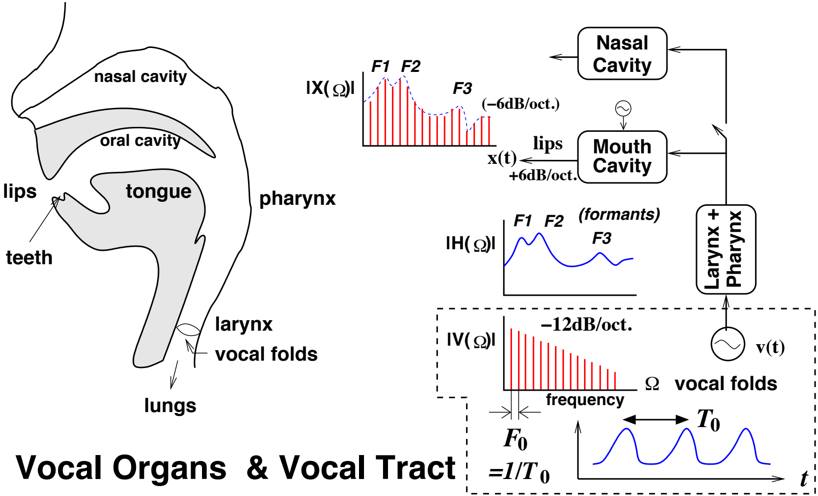



- Frequency bins of STFT are highly correlated each other, i.e. power spectrum representation is highly redundant

# 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

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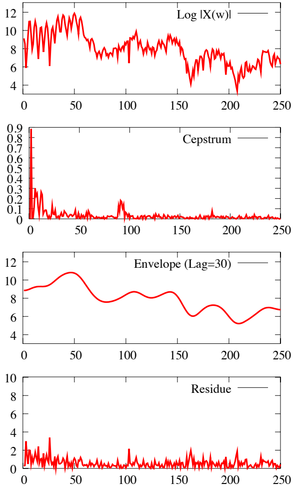
# Cepstral Analysis

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:

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

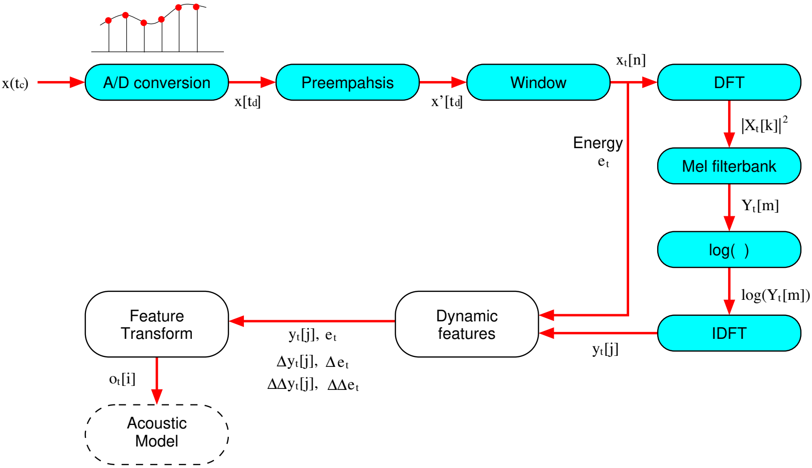
- Since log power spectrum is real and symmetric the inverse DFT is equivalent to a discrete cosine transform (DCT)

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

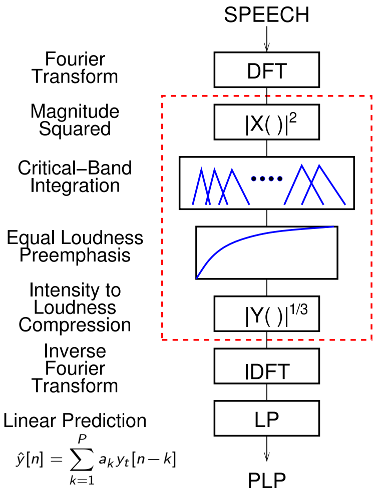
# MFCCs

- 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




- 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

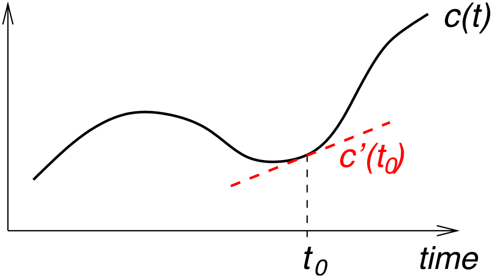
# Dynamic features

- 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 $\Delta$MFCCs, $\Delta$energy
  - 12 $\Delta^2$MFCCs, $\Delta^2$energy

# Estimating dynamic features



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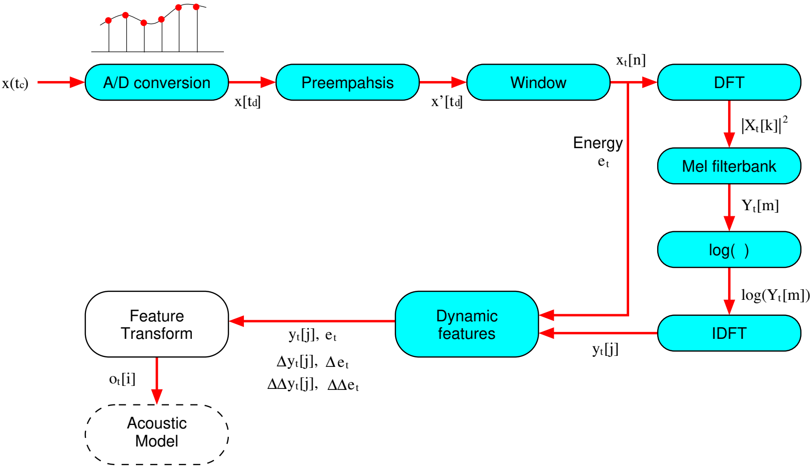
# MFCC-based front end for ASR



# 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+$\Delta$+$\Delta\Delta$ (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.