Extraction and Representation of Features, Spring 2011

Lecture 5: Speech and Audio Analysis

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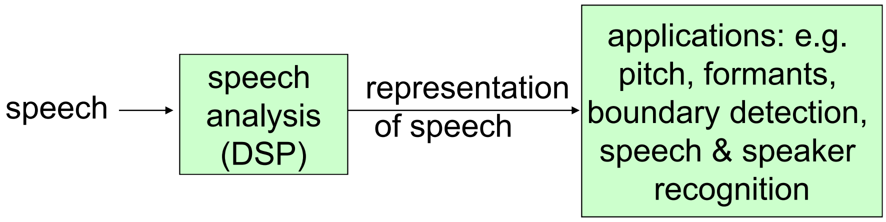
Feature extraction

- A special form of dimensionality reduction, used when the input data is
  - Too large to be stored or processed
  - Redundant (much data, but not much information)
- Data is transformed into a compact representation – a set of features.
- Speech and audio signals have a lot in common.

Speech analysis

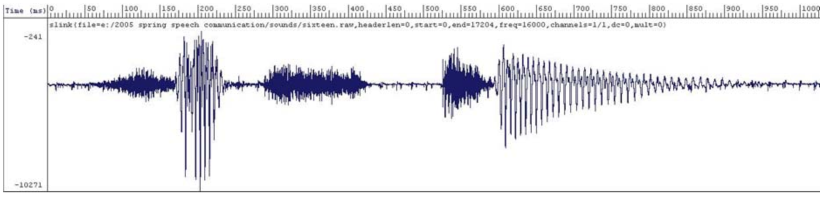
- Most applications of speech processing must exploit the properties of speech signals → Speech Analysis: the process of extracting such properties from a speech signal.



Speech analysis: Short-time analysis

- Short-time speech analysis
- Time-domain processing
- Frequency-domain (spectral) processing
- Linear predictive coding (LPC) analysis
- Cepstral analysis
- Filter bank analysis

Properties of speech signals



Speech is a time-varying signal:

- excitation
- pitch
- amplitude

Short-time processing solution

Assuming that speech has non-time-varying properties (fixed excitation and vocal tract) within short intervals →

Processing short segments (frames) of the speech signal each time

$$f_x(n,m) = x(m)w(n-m)$$

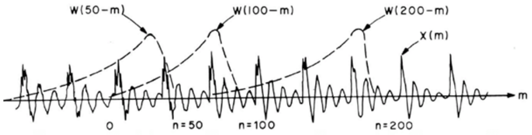
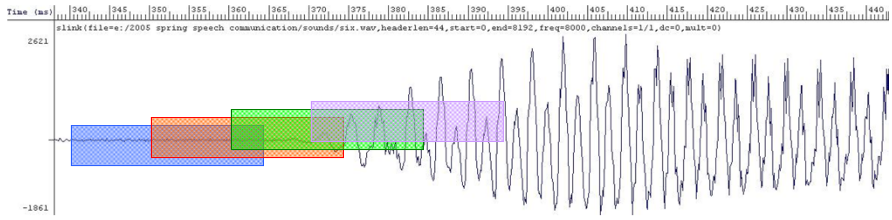


Fig. 6.1 Sketches of $x(m)$ and $w(n-m)$ for several values of n.

Frame-by-frame processing

- Frames often overlap one another

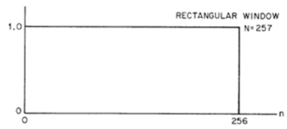


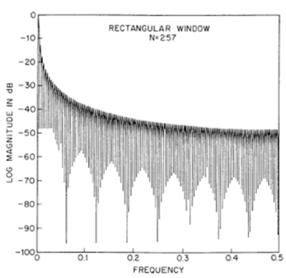
- The frame-based analysis yields a time-varying sequence as a new representation of the speech signal
  - samples at 8000/sec → vectors at 100/sec

Windows

- Rectangular window

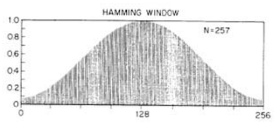
$$w[n] = 1, \qquad 0 \le n \le N-1$$

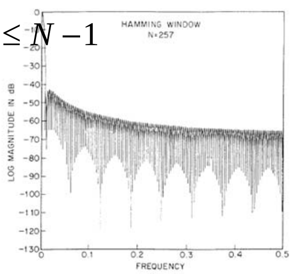




- Hamming window

$$w[n] = 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right), \qquad 0 \le n \le N-1$$





Choice of window

- Window type
  - Bandwidth of Hamming window is about twice the bandwidth of Rectangular
  - Attenuation of more than 40dB for Hamming as compared with 14 dB for Rectangular, outside passband
- Window duration - N
  - Increase N = decrease window bandwidth
  - N should be larger than a pitch period, but smaller than a sound duration

Speech analysis: Time-domain

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Time-domain parameters

- Short-time energy
- Short-time average magnitude
- Short-time zero crossing rate
- Short-time autocorrelation
- Short-time average magnitude difference

Short-time energy

- The long term energy definition is not useful for time-varying signals

$$E = \sum_{m=-\infty}^{\infty} x^2(m)$$

- Short-time energy of weighted signal around *n* is defined as

$$E_n = \sum_{m=-\infty}^{\infty} [x(m)w(n-m)]^2$$

Examples of short-time energy

- It can be used to detection voiced/unvoiced/silence
  - Effects of window type, duration N (bandwidth) and why?

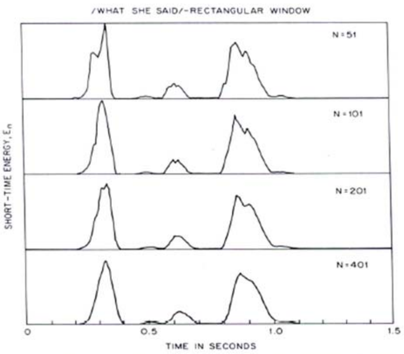


Fig. 4.6 Short-time energy functions for rectangular windows of various lengths.

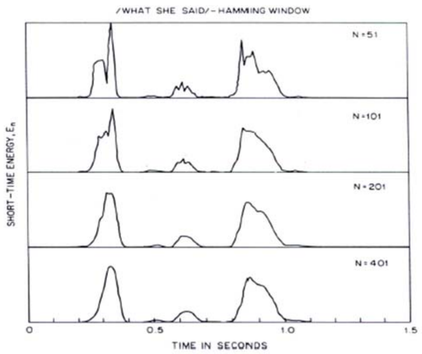


Fig. 4.7 Short-time energy functions for Hamming windows of various lengths.

Uttered by a male speaker.

Two plots converge as N increases.

Short-time magnitude

- Less sensitive to large signal levels as compared to energy where $x^2(n)$ terms is used.

$$M_n = \sum_{m=-\infty}^{\infty} |x(m)|\, w(n-m)$$

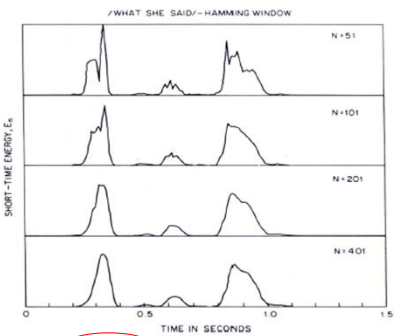


Fig. 4.7 Short-time energy functions for Hamming windows of various lengths.

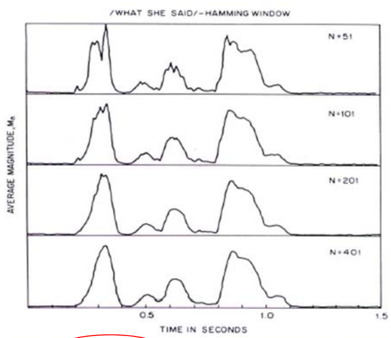
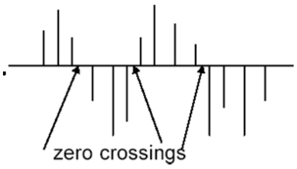


Fig. 4.9 Average magnitude functions for Hamming windows of various lengths.

Short-time average zero-crossing rate

- A zero-crossing occurs if successive samples have different algebraic signs.
- It is a measure of the frequency.
- Definition



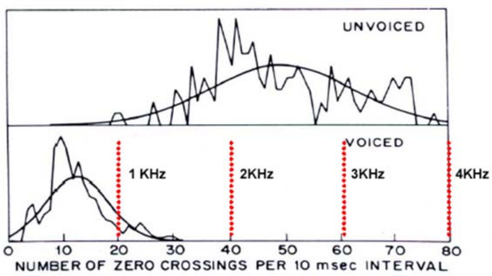
$$Z_n = \sum_{m=-\infty}^{\infty} |\operatorname{sgn}[x(m)] - \operatorname{sgn}[x(m-1)]|\, w(n-m)$$

where
$$\operatorname{sgn}[x(n)] = \begin{cases} 1 & x(n) \geq 0 \\ -1 & x(n) < 0 \end{cases}$$

and
$$w(n) = \begin{cases} \frac{1}{2N} & 0 \leq n \leq N-1 \\ 0 & otherwise \end{cases}$$

Zero-crossing rate distributions

- A histogram of average zero-crossing rates (averaged over 10 msec) for both voiced and unvoiced speech
- In different frequency bands



(80/2)/10ms=4kHz

Fig. 4.11 Distribution of zero-crossings for unvoiced and voiced speech.

Example of zero-crossing rate

- Although the zero-crossing rate varies considerably, the voiced and unvoiced regions are quite prominent.

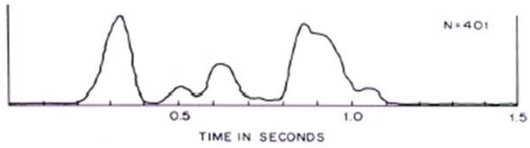


Fig. 4.9 Average magnitude functions for Hamming windows

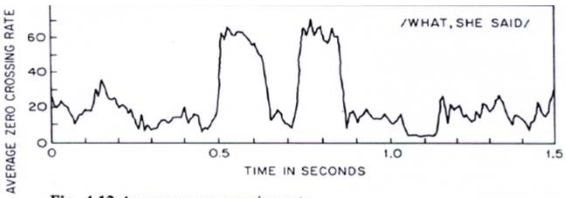


Fig. 4.12 Average zero-crossing rate

Short-time autocorrelation function

- The autocorrelation function

$$\phi(k) = \sum_{m=-\infty}^{\infty} x(m)x(m+k)$$

- The short-time autocorrelation function

$$R_n(k) = \sum_{m=-\infty}^{\infty} x(m)w(n-m)x(m+k)w(n-k-m)$$

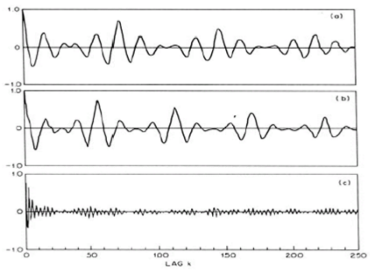


Fig. 4.24 Autocorrelation function for (a) and (b) voiced speech; and (c) unvoiced speech, using a rectangular window with N = 401.

Applications

- Boundary detection
  - short-time energy
  - zero crossing rate
- Pitch estimation
  - short-time autocorrelation function

Speech analysis: Frequency-domain

- Short-time speech analysis
- Time-domain speech processing
- Frequency-domain (spectral) processing
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Discrete-time Fourier transform

$$\begin{cases} X(e^{jw}) = \sum_{n=-\infty}^{+\infty} x[n]e^{-jwn} \\ x[n] = \frac{1}{2\pi}\int_{-\pi}^{\pi} X(e^{jw})e^{jwn}dw \end{cases}$$

Convolution and multiplication duality:

$$\begin{cases} y[n] = x[n] * h[n] \\ Y(e^{jw}) = X(e^{jw})H(e^{jw}) \end{cases}$$

$$\begin{cases} y[n] = x[n]w[n] \\ Y(e^{jw}) = \frac{1}{2\pi}\int_{-\pi}^{\pi} W(e^{j\theta})X(e^{j(w-\theta)})d\theta \end{cases}$$

Short-time Fourier transform

- It is motivated by the need for a spectral representation to reflect the time-varying properties of the speech waveform

$$X_n(e^{jw}) = \sum_{m=-\infty}^{+\infty} w[n-m]x[m]e^{-jwm}$$

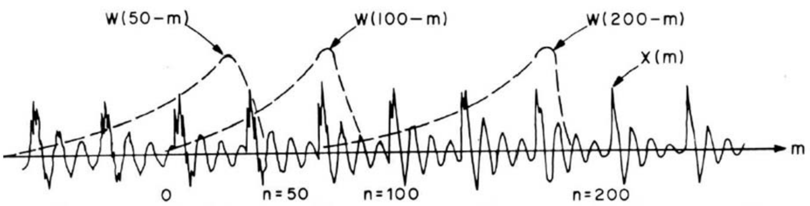
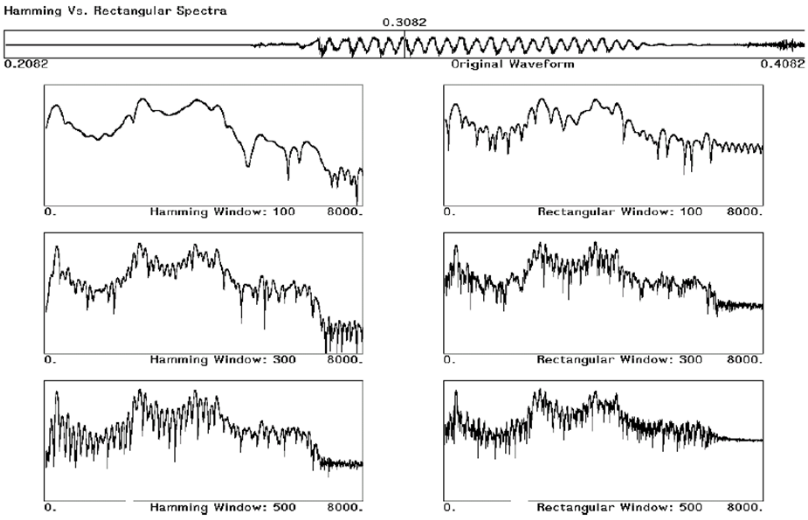


Fig. 6.1 Sketches of $x(m)$ and $w(n-m)$ for several values of n.

Spectra



Spectra of voiced/unvoiced sounds

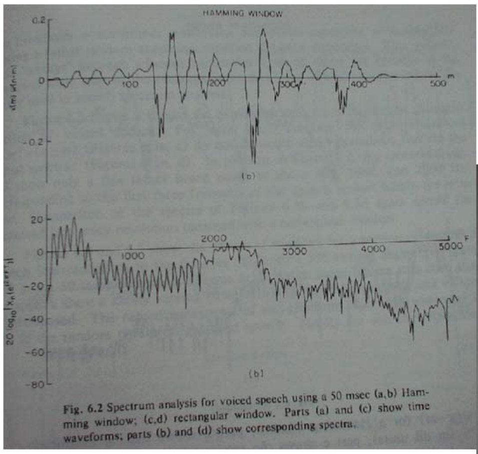


Fig. 6.2 Spectrum analysis for voiced speech using a 50 msec (a,b) Hamming window; (c,d) rectangular window. Parts (a) and (c) show time waveforms; parts (b) and (d) show corresponding spectra.

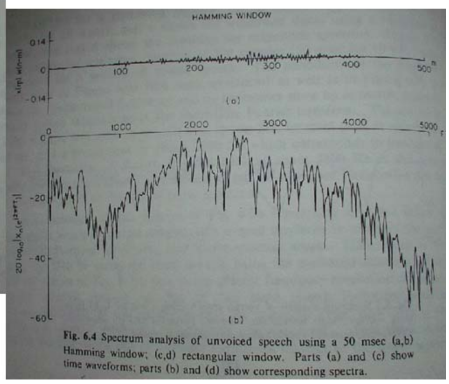
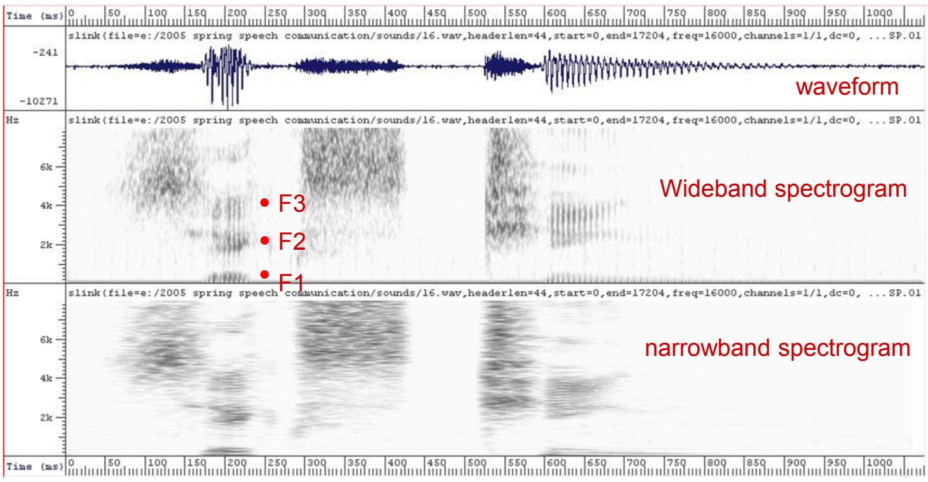


Fig. 6.4 Spectrum analysis of unvoiced speech using a 50 msec (a,b) Hamming window; (c,d) rectangular window. Parts (a) and (c) show time waveforms; parts (b) and (d) show corresponding spectra.

Spectrogram

- Spectrogram
  - two-dimensional waveform (amplitude/time) is converted into a three-dimensional pattern (amplitude/frequency/time)
  - Wideband spectrogram: analyzed on 15ms sections of waveform with a step of 1ms
    - voiced regions with vertical striations due to the periodicity of the time waveform (each vertical line represents a pulse of vocal folds) while unvoiced regions are solid/random, or 'snowy'
  - Narrowband spectrogram: on 50ms
    - pitch for voiced intervals in horizontal lines

Wide- and narrow-band spectrograms



Speech analysis: LPC analysis

- Short-time speech analysis
- Time-domain speech processing
- Frequency-domain (spectral) processing
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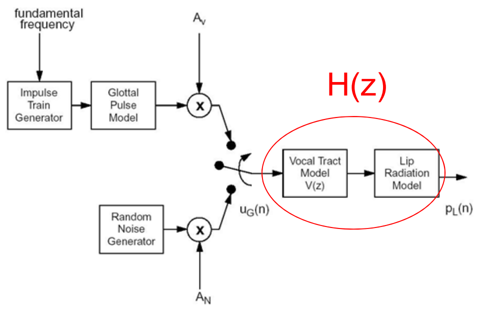
Discrete-time filter model for speech

Its philosophy is related to the speech model in which speech is modelled as the output of a linear, time-varying system excited by either quasi-periodic pulses or random noise.

The LPC provides a robust and accurate method for estimating the parameters of the time-varying system.



LPC analysis

- For efficient coding, speech signals are often modelled using parameters of the vocal tract shape that generates them.
- Pole-zero model (ideal during a stationary frame)

$$H(z) = \frac{S(z)}{U(z)} = G\frac{1+\sum_{l=1}^{q} b_l z^{-l}}{1-\sum_{k=1}^{p} a_k z^{-k}}$$

- All-pole model (simple): a matter of analytical necessity

$$H(z) = \frac{S(z)}{U(z)} = G\frac{1}{1-\sum_{k=1}^{p} a_k z^{-k}}$$

one zero ↔ multiple poles

$$1 - az^{-1} = \frac{1}{\sum_{n=0}^{\infty} a^n z^{-n}}$$

All-pole model – the LPC model

$$H(z) = \frac{S(z)}{U(z)} = G\frac{1}{1-\sum_{k=1}^{p} a_k z^{-k}} \rightarrow S(z) = \frac{G}{1-\sum_{k=1}^{p} a_k z^{-k}} U(z)$$

$$\rightarrow \quad S(z) = S(z)\sum_{k=1}^{p} a_k z^{-k} + GU(z)$$

$$\rightarrow \quad s(n) = \sum_{k=1}^{p} a_k s(n-k) + Gu(n)$$

where u(n) is a normalised excitation and G is the gain of the excitation

The LPC model

After excluding the excitation term, a given speech sample at time *n*, *s*(*n*), can be approximated as a linear combination of the past *p* speech samples:

$$\tilde{s}(n) = \alpha_1 s(n-1) + \alpha_2 s(n-2) + \ldots + \alpha_p s(n-p)$$

where the coefficients $\alpha_1, \alpha_2, \ldots, \alpha_p$ are assumed constant over the speech frame.

LPC analysis: to determine a set of predictor coefficients $\{\alpha_k\}$ directly from the speech signal.

LPC analysis equations

Windowed speech: $x(n) = s(n)w(n)$

Error of linear predictor $e(n) = s(n) - \hat{s}(n)$

$$e(n) = s(n) - \sum_{k=1}^{p} \alpha_k s(n-k)$$

Method: minimise mean-squared prediction error

Short-time average prediction error

$$E_n = \sum_{m=-\infty}^{\infty} e_n^2(m) = \sum_{m=-\infty}^{\infty} [s_n(m) - \sum_{k=1}^{p} \alpha_k s_n(m-k)]^2$$

LPC analysis equations (cont'd)

Find α_k such that E_n is minimal

$$E_n = \sum_{m=-\infty}^{\infty} e_n^2(m) = \sum_{m=-\infty}^{\infty} [s_n(m) - \sum_{k=1}^{p} \alpha_k s_n(m-k)]^2$$

$$\frac{\partial E_n}{\partial \alpha_i} = 0 \text{ for } i = 1,2,\ldots,p$$

Resulting in $\sum_{m=-\infty}^{\infty} s_n(m-i)s_n(m) = \sum_{k=1}^{p} \hat{\alpha}_k \sum_{m=-\infty}^{\infty} s_n(m-i)s_n(m-k)$

Define covariance $\phi_n(i,k) = \sum_{m=-\infty}^{\infty} s_n(m-i)s_n(m-k)$

Then

$$\sum_{k=1}^{p} \hat{\alpha}_k \phi_n(i,k) = \phi_n(i,0) \quad i = 1,2,\ldots,p$$

Short-time LP analysis

- To solve the following equation for the optimum predictor coefficients (the $\hat{\alpha}_k$ s)

$$\phi(i,0) = \sum_{k=1}^{p} \hat{a}_k \phi(i,k) \quad i = 1,2,\ldots,p$$

we have to compute $\phi(i,k)$ and then solve the resulting set of p equations.

Speech analysis: Cepstral analysis

- Short-time speech analysis
- Time-domain speech processing
- Frequency-domain (spectral) processing
- Linear predictive coding (LPC) analysis
- Cepstral analysis
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Homomorphic speech processing

- Again, speech is modelled as the output of a linear, time-varying system (linear time-invariant (LTI) in short seg.) excited by either quasi-periodic pulses or random noise.
- The problem of speech analysis is to estimate the parameters of the speech model and to measure their variations with time.
- Since the excitation and impulse response of a LTI system are combined in a convolutional manner, the problem of speech analysis can also been viewed as a problem in separating the components of a convolution, called ”deconvolution”.

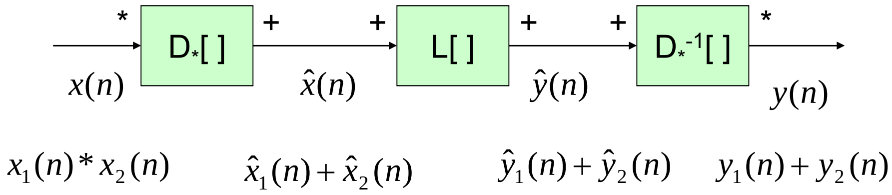
$$y[n] = x[n] * h[n]$$

Homomorphic deconvolution

- Converts a convolution into a sum

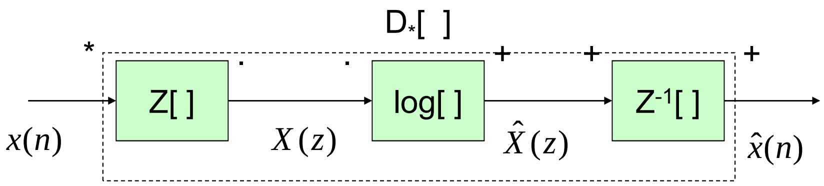
$$\begin{cases} y(n) = x(n) * h(n) \\ \hat{y}(n) = \hat{x}(n) + \hat{h}(n) \end{cases}$$

- Canonic form for system for homomorphic deconvolution



The characteristic system

- The characteristic system for homomorphic deconvolution



Cepstral analysis

Observation:

$$x[n] = x_1[n] * x_2[n] \Leftrightarrow X(z) = X_1(z)X_2(z)$$

taking logarithm of X(z), then

$$\log\{X(z)\} = \log\{X_1(z)\} + \log\{X_2(z)\}$$

$$\text{i.e.,}\ \hat{X}(z) = \hat{X}_1(z) + \hat{X}_2(z)$$

$\leftarrow\rightarrow$ $\hat{x}[n] = \hat{x}_1[n] + \hat{x}_2[n]$

So, the two convolved signals are additive.

Complex cepstrum and real cepstrum

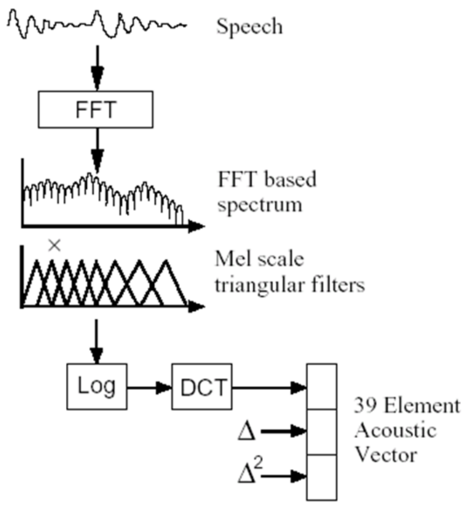
Real cepstrum $c[n]$ is the even part of $\hat{x}[n]$

$$\begin{cases} \hat{x}[n] = \dfrac{1}{2\pi}\displaystyle\int_{-\pi}^{\pi} \hat{X}(e^{jw})e^{jwn}dw \\ \qquad = \dfrac{1}{2\pi}\displaystyle\int_{-\pi}^{\pi} \log\{X(e^{jw})\}e^{jwn}dw \qquad \text{complex cepstrum} \\ c[n] = \dfrac{1}{2\pi}\displaystyle\int_{-\pi}^{\pi} \log|X(e^{jw})|\, e^{jwn}dw \qquad \text{cepstrum} \end{cases}$$

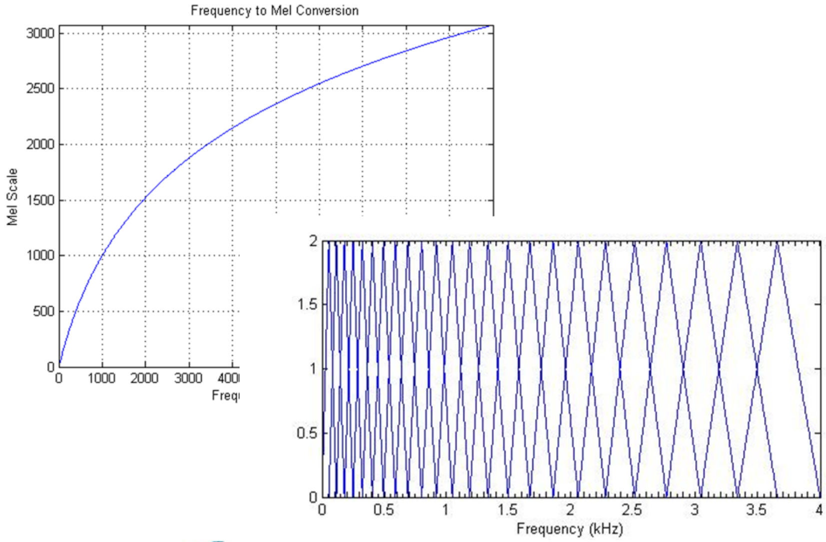
- *ceps*trum was coined by reversing the first syllable in the word *spec*trum.

Mel-frequency cepstral coefficience

MFCC



Mel-frequency filter bank



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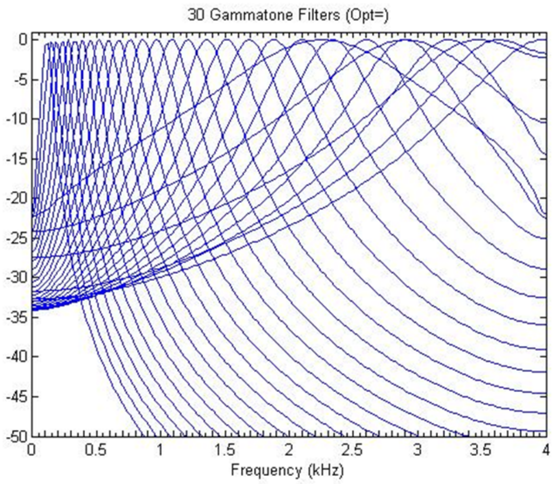
Gammatone filters

- Gammatone is a widely used model of auditory filters.
- Impulse response (the product of a gamma distribution and sinusoidal tone):

$$g(t) = at^{n-1}e^{-2\pi bt}\cos(2\pi ft + \phi),$$

where *f* is the frequency, φ is the phase of the carrier (tone), *a* is the amplitude, *n* is the filter's order, *b* is the filter's bandwidth, and *t* is time.

Gammatone filters



Summary

- Short-time speech analysis
- Time-domain processing
- Frequency-domain (spectral) processing
- Linear predictive coding (LPC) analysis
- Cepstral analysis
- Filter bank analysis