EE E6820: Speech & Audio Processing & Recognition

Lecture 5: Speech modeling

Dan Ellis <dpwe@ee.columbia.edu>
Michael Mandel <mim@ee.columbia.edu>

Columbia University Dept. of Electrical Engineering
http://www.ee.columbia.edu/∼dpwe/e6820

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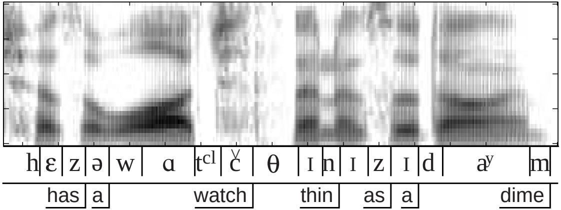
1. Modeling speech signals
2. Spectral and cepstral models
3. Linear predictive models (LPC)
4. Other signal models
5. Speech synthesis

Outline

The speech signal



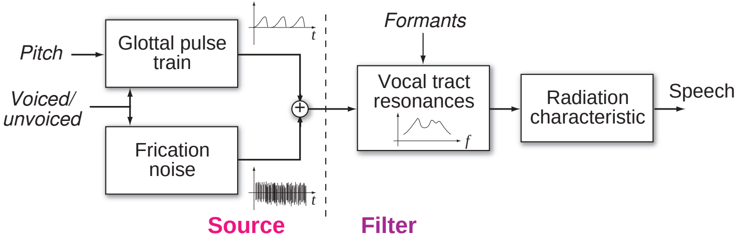
Elements of the speech signal

- spectral resonances (formants, moving)
- periodic excitation (voicing, pitched) + pitch contour
- noise excitation
- transients (stop-release bursts)
- amplitude modulation (nasals, approximants)
- timing!

The source-filter model

Notional separation of

- source: excitation, fine time-frequency structure
- filter: resonance, broad spectral structure



More a modeling approach than a single model

Signal modeling

- Signal models are a kind of representation
  - to make some aspect explicit
  - for efficiency
  - for flexibility
- Nature of model depends on goal
  - classification: remove irrelevant details
  - coding/transmission: remove perceptual irrelevance
  - modification: isolate control parameters
- But commonalities emerge
  - perceptually irrelevant detail (coding) will also be irrelevant for classification
  - modification domain will usually reflect 'independent' perceptual attributes
  - getting at the abstract information in the signal

Different influences for signal models

- Receiver
  - see how signal is treated by listeners

    $\longrightarrow$ cochlea-style filterbank models ...
- Transmitter (source)
  - physical vocal apparatus can generate only a limited range of signals ...

    $\longrightarrow$ LPC models of vocal tract resonances
- Making explicit particular aspects
  - compact, separable correlates of resonances

    $\longrightarrow$ cepstrum
  - modeling prominent features of NB spectrogram

    $\longrightarrow$ sinusoid models
  - addressing unnaturalness in synthesis

    $\longrightarrow$ Harmonic+noise model

Application of (speech) signal models

- Classification / matching
  Goal: highlight important information
  - speech recognition (lexical content)
  - speaker recognition (identity or class)
  - other signal classification
  - content-based retrieval
- Coding / transmission / storage
  Goal: represent just enough information
  - real-time transmission, *e.g.* mobile phones
  - archive storage, *e.g.* voicemail
- Modification / synthesis
  Goal: change certain parts independently
  - speech synthesis / text-to-speech (change the words)
  - speech transformation / disguise (change the speaker)

Outline

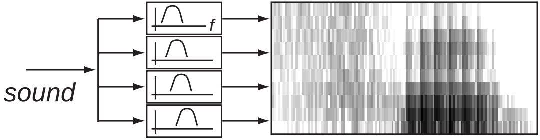
Spectral and cepstral models

- Spectrogram seems like a good representation
  - long history
  - satisfying in use
  - experts can 'read' the speech
- What is the information?
  - intensity in time-frequency cells
  - typically 5ms $\times$ 200 Hz $\times$ 50 dB

$\longrightarrow$ Discarded detail:
  - phase
  - fine-scale timing
- The starting point for other representations

Short-time Fourier transform (STFT) as filterbank

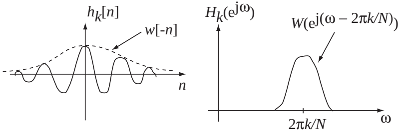
View spectrogram rows as coming from separate bandpass filters



Mathematically:

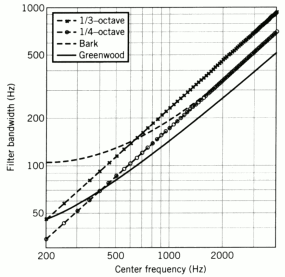
$$X[k, n_0] = \sum_n x[n] w[n - n_0] \exp\left(-j \frac{2\pi k(n - n_0)}{N}\right)$$
$$= \sum_n x[n] h_k[n_0 - n]$$

where $h_k[n] = w[-n] \exp\left(j \frac{2\pi kn}{N}\right)$



Spectral models: which bandpass filters?

- Constant bandwidth? (analog / FFT)
- But: cochlea physiology & critical bandwidths
  - $\longrightarrow$ implement ear models with bandpass filters & choose bandwidths by *e.g.* CB estimates
- Auditory frequency scales
  - constant 'Q' (center freq / bandwidth), mel, Bark, ...

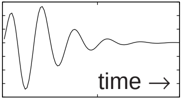


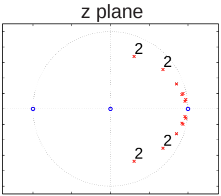
Gammatone filterbank

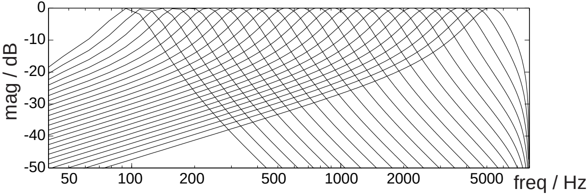
- Given bandwidths, which filter shapes?
  - match inferred temporal integration window
  - match inferred spectral shape (sharp high-freq slope)
  - keep it simple (since it's only approximate)

$\longrightarrow$ Gammatone filters
  - 2N poles, 2 zeros, low complexity
  - reasonable linear match to cochlea

$$h[n] = n^{N-1} e^{-bn} \cos(\omega_i n)$$

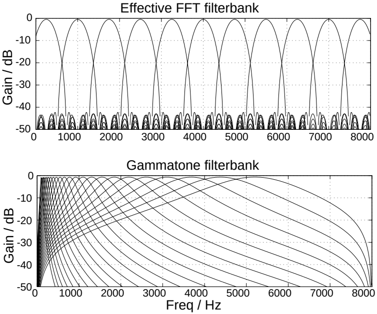




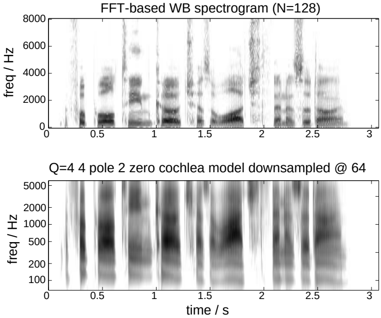


Constant-BW vs. cochlea model

Frequency responses



Spectrograms



Magnitude smoothed over 5-20 ms time window

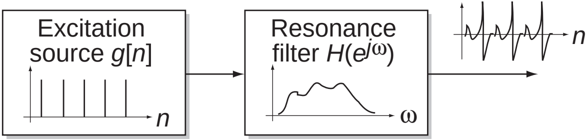
Limitations of spectral models

- Not much data thrown away
  - just fine phase / time structure (smoothing)
  - little actual 'modeling'
  - still a large representation
- Little separation of features

  e.g. formants and pitch
- Highly correlated features
  - modifications affect multiple parameters
- But, quite easy to reconstruct
  - iterative reconstruction of lost phase

The cepstrum

- Original motivation: assume a source-filter model:



- Define 'Homomorphic deconvolution':

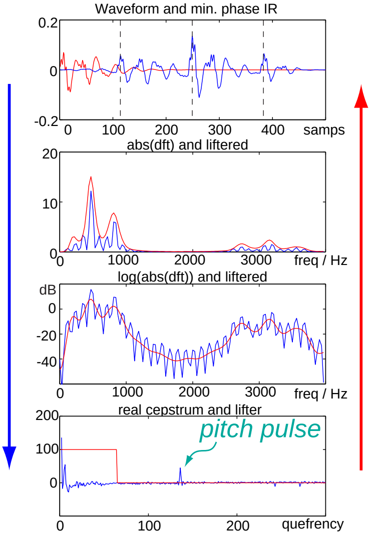
source-filter convolution	$g[n] * h[n]$
FT $\rightarrow$ product	$G(e^{j\omega})H(e^{j\omega})$
log $\rightarrow$ sum	$\log G(e^{j\omega}) + \log H(e^{j\omega})$
IFT $\rightarrow$ separate fine structure	$c_g[n] + c_h[n]$
$=$ deconvolution	

- Definition

  Real cepstrum $c_n = \mathrm{idft}\left(\log\left|\mathrm{dft}(x[n])\right|\right)$

Stages in cepstral deconvolution

- Original waveform has excitation fine structure convolved with resonances
- DFT shows harmonics modulated by resonances
- Log DFT is sum of harmonic 'comb' and resonant bumps
- IDFT separates out resonant bumps (low quefrency) and regular, fine structure ('pitch pulse')
- Selecting low-n cepstrum separates resonance information (deconvolution / 'liftering')



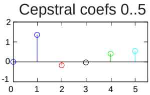
Properties of the cepstrum

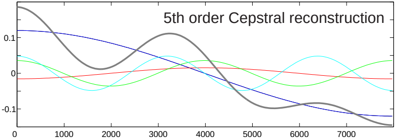
- Separate source (fine) from filter (broad structure)
  - smooth the log magnitude spectrum to get resonances
- Smoothing spectrum is filtering along frequency

  i.e. convolution applied in Fourier domain

  $\rightarrow$ *multiplication* in IFT ('liftering')
- Periodicity in time $\rightarrow$ harmonics in spectrum $\rightarrow$ 'pitch pulse' in high-n cepstrum
- Low-n cepstral coefficients are DCT of broad filter / resonance shape

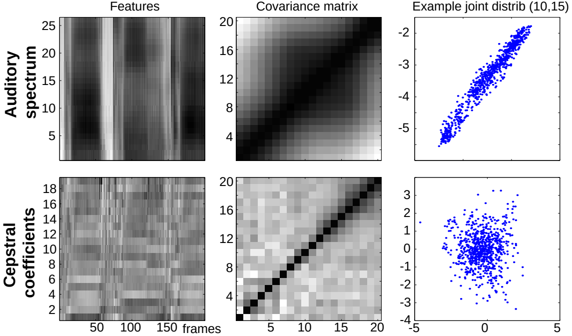
$$c_n = \int \log \left| X(e^{j\omega}) \right| (\cos n\omega + \cancel{j \sin n\omega})\, d\omega$$





Aside: correlation of elements

- Cepstrum is popular in speech recognition
  - feature vector elements are decorrelated



  - c_0 'normalizes out' average log energy
- Decorrelated pdfs fit diagonal Gaussians
  - simple correlation is a waste of parameters
- DCT is close to PCA for (mel) spectra?

Outline

Linear predictive modeling (LPC)

- LPC is a very successful speech model
  - it is mathematically efficient (IIR filters)
  - it is remarkably accurate for voice (fits source-filter distinction)
  - it has a satisfying physical interpretation (resonances)
- Basic math
  - model output as linear function of prior outputs:

$$s[n] = \left(\sum_{k=1}^{p} a_k s[n-k] \right) + e[n]$$

    ... hence "linear prediction" (p^{th} order)
  - $e[n]$ is excitation (input), AKA prediction error

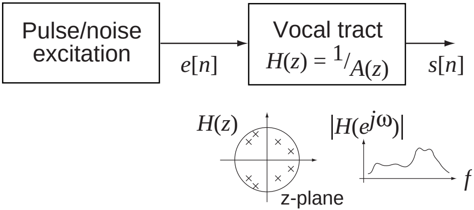
$$\Rightarrow \frac{S(z)}{E(z)} = \frac{1}{1 - \sum_{k=1}^{p} a_k z^{-k}} = \frac{1}{A(z)}$$

... all-pole modeling, 'autoregression' (AR) model

Vocal tract motivation for LPC

- Direct expression of source-filter model

$$s[n] = \left(\sum_{k=1}^{p} a_k s[n-k] \right) + e[n]$$



- Acoustic tube models suggest all-pole model for vocal tract
- Relatively slowly-changing
  - update $A(z)$ every 10-20 ms
- Not perfect: Nasals introduce zeros

Estimating LPC parameters

- Minimize short-time squared prediction error

$$E = \sum_{n=1}^{m} e^2[n] = \sum_{n} \left(s[n] - \sum_{k=1}^{p} a_k s[n-k] \right)^2$$

- Differentiate w.r.t. a_k to get equations for each k:

$$0 = \sum_{n} 2 \left(s[n] - \sum_{j=1}^{p} a_j s[n-j] \right) (-s[n-k])$$

$$\sum_{n} s[n]s[n-k] = \sum_{j} a_j \sum_{n} s[n-j]s[n-k]$$

$$\phi(0,k) = \sum_{j} a_j \phi(j,k)$$

- where $\phi(j,k) = \sum_{n=1}^{m} s[n-j]s[n-k]$ are correlation coefficients
    - p linear equations to solve for all a_js ...

Evaluating parameters

- Linear equations $\phi(0,k) = \sum_{j=1}^{p} a_j \phi(j,k)$
- If $s[n]$ is assumed to be zero outside of some window

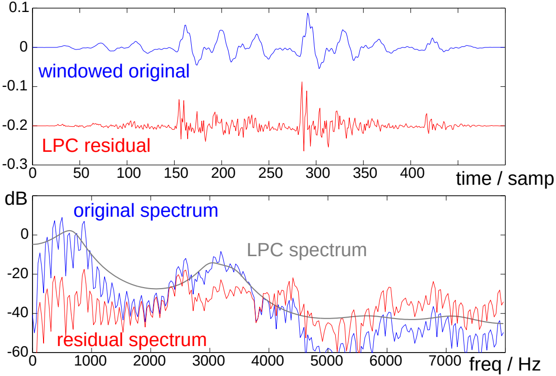
$$\phi(j,k) = \sum_n s[n-j]s[n-k] = r_{ss}(|j-k|)$$

  - $r_{ss}(\tau)$ is autocorrelation
- Hence equations become:

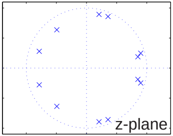
$$\begin{bmatrix} r(1) \\ r(2) \\ \vdots \\ r(p) \end{bmatrix} = \begin{bmatrix} r(0) & r(1) & \cdots & r(p-1) \\ r(1) & r(2) & \cdots & r(p-2) \\ \vdots & \vdots & \ddots & \vdots \\ r(p-1) & r(p-2) & \cdots & r(0) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_p \end{bmatrix}$$

- Toeplitz matrix (equal antidiagonals)
  $\rightarrow$ can use Durbin recursion to solve
- (Solve full $\phi(j,k)$ via Cholesky)

LPC illustration



Actual poles



Interpreting LPC

- Picking out resonances
  - if signal really was source + all-pole resonances, LPC should find the resonances
- Least-squares fit to spectrum
  - minimizing $e^2[n]$ in time domain is the same as minimizing $E^2(e^{j\omega})$ by Parseval

  $\rightarrow$ close fit to spectral peaks; valleys don't matter
- Removing smooth variation in spectrum
  - $\frac{1}{A(z)}$ is a low-order approximation to $S(z)$
  - $\frac{S(z)}{E(z)} = \frac{1}{A(z)}$
  - hence, residual $E(z) = A(z)S(z)$ is a 'flat' version of S
- Signal whitening:
  - white noise (independent $x[n]$s) has flat spectrum

  $\rightarrow$ whitening removes temporal correlation

Alternative LPC representations

- Many alternate p-dimensional representations
  - coefficients $\{a_j\}$
  - roots $\{\lambda_j\}$: $\prod \left(1 - \lambda_j z^{-j}\right) = 1 - \sum a_j z^{-1}$
  - line spectrum frequencies...
  - reflection coefficients $\{k_j\}$ from lattice form
  - tube model log area ratios $g_j = \log\left(\frac{1-k_j}{1+k_j}\right)$
- Choice depends on:
  - mathematical convenience / complexity
  - quantization sensitivity
  - ease of guaranteeing stability
  - what is made explicit
  - distributions as statistics

LPC applications

- Analysis-synthesis (coding, transmission)
  - $S(z) = \frac{E(z)}{A(z)}$ hence can reconstruct by filtering $e[n]$ with $\{a_j\}$s
  - whitened, decorrelated, minimized $e[n]$s are easy to quantize

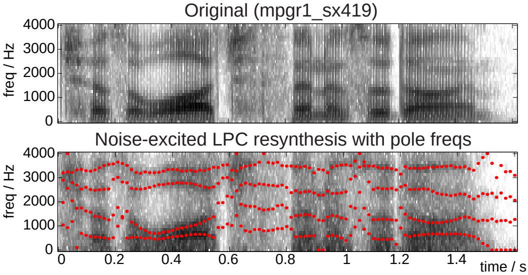
  ... or can model $e[n]$ *e.g.* as simple pulse train
- Recognition / classification
  - LPC fit responds to spectral peaks (formants)
  - can use for recognition (convert to cepstra?)
- Modification
  - separating source and filter supports cross-synthesis
  - pole / resonance model supports 'warping'

    e.g. male $\rightarrow$ female

Aside: Formant tracking

- Formants carry (most?) linguistic information
- Why not classify → speech recognition?

  e.g. local maxima in cepstral-liftered spectrum pole frequencies in LPC fit
- But: recognition needs to work in *all* circumstances
  - formants can be obscured or undefined

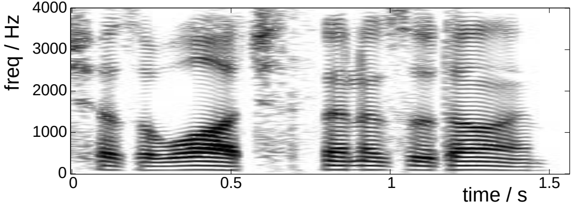


→ need more graceful, robust parameters

Outline

Sinusoid modeling

- Early signal models required low complexity
  e.g. LPC
- Advances in hardware open new possibilities. . .
- NB spectrogram suggests harmonics model



  - 'important' info in 2D surface is set of tracks?
  - harmonic tracks have ∼smooth properties
  - straightforward resynthesis

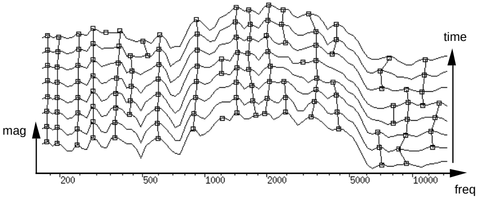
Sine wave models

- Model sound as sum of AM/FM sinusoids

$$s[n] = \sum_{k=1}^{N[n]} A_k[n] \cos(n\,\omega_k[n] + \phi_k[n])$$

  - A_k, ω_k, ϕ_k piecewise linear or constant
  - can enforce harmonicity: $\omega_k = k\omega_0$

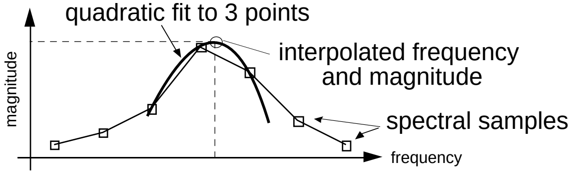
- Extract parameters directly from STFT frames:



  - find local maxima of $|S[k, n]|$ along frequency
  - track birth/death and correspondence

Finding sinusoid peaks

- Look for local maxima along DFT frame
  i.e. $|s[k-1,n]| < |S[k,n]| > |S[k+1,n]|$
- Want exact frequency of implied sinusoid
  - DFT is normally quantized quite coarsely
  e.g. 4000 Hz / 256 bands = 15.6 Hz/band



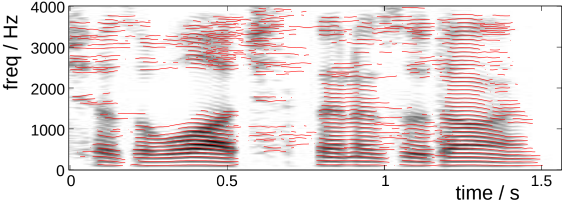
  - may also need interpolated unwrapped phase
- Or, use differential of phase along time (pvoc):

$$\omega = \frac{a\dot{b} - b\dot{a}}{a^2 + b^2} \qquad \text{where } S[k,n] = a + jb$$

Sinewave modeling applications

- Modification (interpolation) and synthesis
  - connecting arbitrary ω and ϕ requires cubic phase interpolation (because $\omega = \dot{\phi}$)
- Types of modification
  - time and frequency scale modification

    ... with or without changing formant envelope
  - concatenation / smoothing boundaries
  - phase realignment (for crest reduction)
- Non-harmonic signals? OK-ish

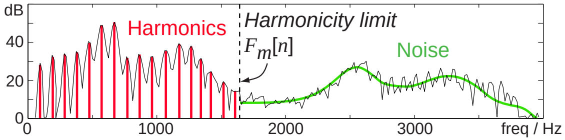


Harmonics + noise model

- Motivation to improve sinusoid model because
  - problems with analysis of real (noisy) signals
  - problems with synthesis quality (esp. noise)
  - perceptual suspicions
- Model

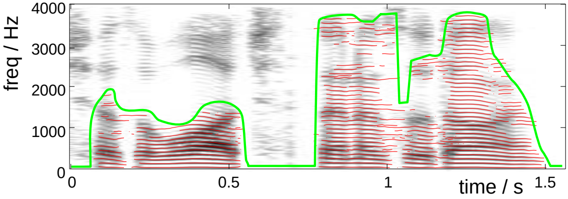
$$s[n] = \sum_{k=1}^{N[n]} \underbrace{A_k[n] \cos(nk\omega_0[n])}_{\text{Harmonics}} + \underbrace{e[n](h_n[n] * b[n])}_{\text{Noise}}$$

  - sinusoids are forced to be harmonic
  - remainder is filtered and time-shaped noise
- 'Break frequency' $F_m[n]$ between H and N

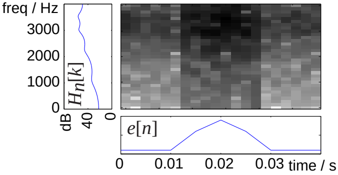


HNM analysis and synthesis

Dynamically adjust $F_m[n]$ based on 'harmonic test':



Noise has envelopes in time $e[n]$ and frequency H_n

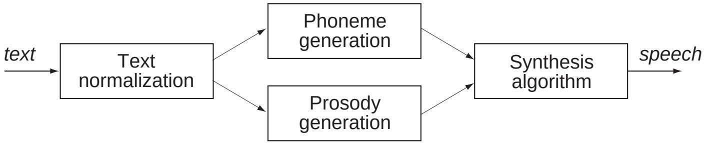


- reconstruct bursts / synchronize to pitch pulses

Outline

Speech synthesis

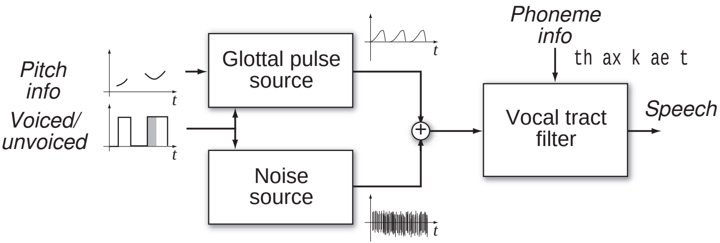
- One thing you can do with models
- Synthesis easier than recognition?
  - listeners do the work
  - ... but listeners are very critical
- Overview of synthesis



  - normalization disambiguates text (abbreviations)
  - phonetic realization from pronunciation dictionary
  - prosodic synthesis by rule (timing, pitch contour)
  - ... all control waveform generation

Source-filter synthesis

Flexibility of source-filter model is ideal for speech synthesis

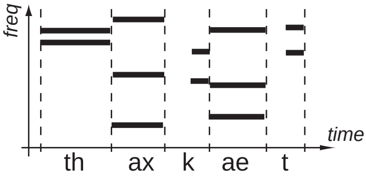


Excitation source issues

- voiced / unvoiced / mixture ([th] *etc.*)
- pitch cycles of voiced segments
- glottal pulse shape → voice quality?

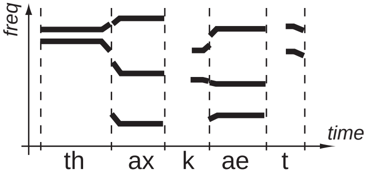
Vocal tract modeling

Simplest idea: store a single VT model for each phoneme



- but discontinuities are very unnatural

Improve by smoothing between templates



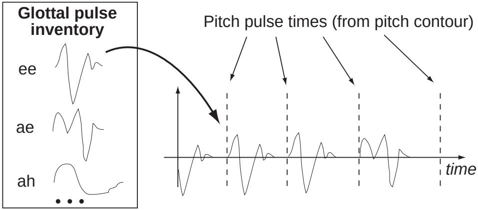
- trick is finding the right domain

Cepstrum-based synthesis

- Low-n cepstrum is compact model of target spectrum
- Can invert to get actual VT IR waveforms:

$$c_n = \mathrm{idft}(\log |\mathrm{dft}(x[n])|)$$
$$\Rightarrow h[n] = \mathrm{idft}(\exp(\mathrm{dft}(c_n)))$$

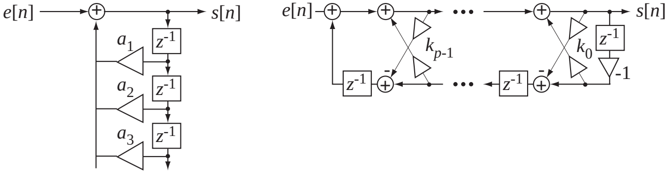
- All-zero (FIR) VT response
  $\rightarrow$ can pre-convolve with glottal pulses



  - cross-fading between templates OK

LPC-based synthesis

- Very compact representation of target spectra
  - 3 or 4 pole pairs per template
- Low-order IIR filter → very efficient synthesis
- How to interpolate?
  - cannot just interpolate a_j in a running filter
  - but lattice filter has better-behaved interpolation

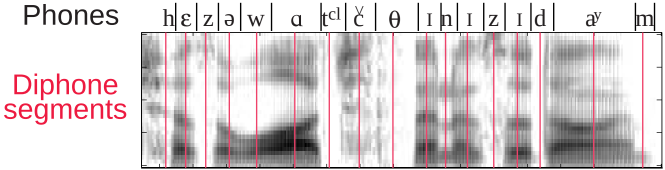


- What to use for excitation
  - residual from original analysis
  - reconstructed periodic pulse train
  - parametrized residual resynthesis

Diphone synthesis

- Problems in phone-concatenation synthesis
  - phonemes are context-dependent
  - coarticulation is complex
  - transitions are critical to perception

→ store transitions instead of just phonemes

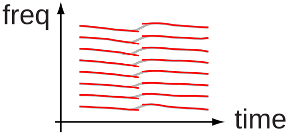


  - ∼ 40 phones ⇒ ∼ 800 diphones
  - or even more context if have larger database

- How to splice diphones together?
  - TD-PSOLA: align pitch pulses and cross fade
  - MBROLA: normalized multiband

HNM synthesis

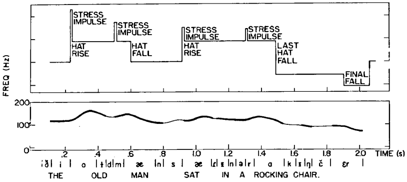
- High quality resynthesis of real diphone units + parametric representation for modification
  - pitch, timing modifications
  - removal of discontinuities at boundaries
- Synthesis procedure
  - linguistic processing gives phones, pitch, timing
  - database search gives best-matching units
  - use HNM to fine-tune pitch and timing
  - cross-fade A_k and ω_0 parameters at boundaries



- Careful preparation of database is key
  - sine models allow phase alignment of all units
  - larger database improves unit match

Generating prosody

- The real factor limiting speech synthesis?
- Waveform synthesizers have inputs for
  - intensity (stress)
  - duration (phrasing)
  - fundamental frequency (pitch)
- Curves produced by superposition of (many) inferred linguistic rules
  - phrase final lengthening, unstressed shortening, ...



- Or learn rules from transcribed elements

Summary

- Range of models
  - spectral, cepstral
  - LPC, sinusoid, HNM
- Range of applications
  - general spectral shape (filterbank) $\rightarrow$ ASR
  - precise description (LPC + residual) $\rightarrow$ coding
  - pitch, time modification (HNM) $\rightarrow$ synthesis
- Issues
  - performance vs computational complexity
  - generality vs accuracy
  - representation size vs quality

Parting thought

not all parameters are created equal...

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