Speech Modifications

Lecture 3: Harmonic plus Noise Models and Modifications

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History

- MBE (Griffin et al.1988 [1])
- Sinusoids plus band-pass random signals (Abrantes et al.1991 [2]
- Harmonic and Stochastic Model (Laroche et al.1993 [3]
- Iterative decomposition of the excitation signal (Yegnayarayana et al.1995 [4])
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Why to decompose?

Decomposing speech into (quasi)periodic and non-periodic part has many applications in:

- Speech modification
- Speech coding
- Pathologic voice detection (i.e., HNR ...)
- Psychoacoustic research

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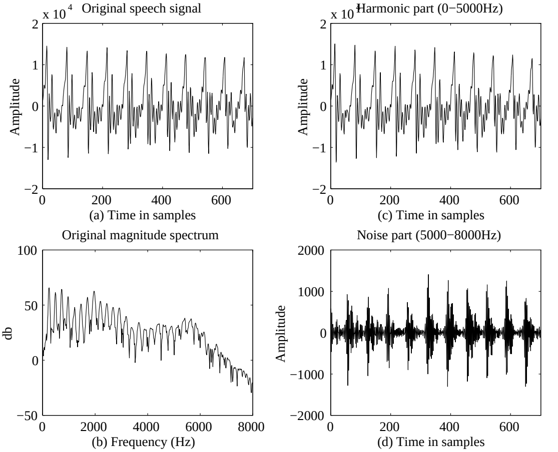
Motivation for HNM



Brief overview of HNM

- HNM is a pitch-synchronous harmonic plus noise representation of the speech signal.
- Speech spectrum is divided into a low and a high band delimited by the so-called maximum voiced frequency.
- The low band of the spectrum (below the maximum voiced frequency) is represented solely by harmonically related sine waves.
- The upper band is modeled as a noise component modulated by a time-domain amplitude envelope.
- HNM allows high-quality copy synthesis and prosodic modifications.

HNM IN EQUATIONS

- Harmonic part:

$$h(t) = \sum_{k=-L(t)}^{L(t)} A_k(t) e^{j\,k\omega_0(t)\,t}$$

- Noise part:

$$n(t) = e(t)\,[v(\tau, t) \star b(t)]$$

- Speech:

$$s(t) = h(t) + n(t)$$

Periodic part

- HNM_1: Sum of exponential functions without slope

$$h_1[n] = \sum_{k=-L(n_a^i)}^{L(n_a^i)} a_k(n_a^i) e^{j2\pi k f_0(n_a^i)(n-n_a^i)}$$

- HNM_2: Sum of exponential function with complex slope

$$h_2[n] = \Re\left\{\sum_{k=1}^{L(n_a^i)} A_k(n) \exp^{j2\pi k f_0(n_a^i)(n-n_a^i)}\right\}$$

where

$$A_k(n) = a_k(n_a^i) + (n - n_a^i) b_k(n_a^i)$$

with $a_k(n_a^i), b_k(n_a^i)$ to be complex numbers (amplitude and slope respectively). $\Re$ denotes taking the real part.

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Periodic part *continuing*

- HNM_3: Sum of sinusoids with time-varying real amplitudes

$$h_3[n] = \sum_{k=0}^{L(n_a^i)} a_k(n) cos(\varphi_k(n))$$

where

$$\begin{aligned} a_k(n) &= c_{k0} + c_{k1}\,(n - n_a^i)^1 + \cdots + c_{kp}\,(n - n_a^i)^{p(n)} \\ \varphi_k(n) &= \epsilon_k + 2\pi\, k\zeta\,(n - n_a^i) \end{aligned}$$

where $p(n)$ is the order of the amplitude polynomial, which is, in general, a time-varying parameter.

Residual (Noise) part

The non-periodic part is just the *residual* signal obtained by subtracting the periodic-part (harmonic part) from the original speech signal in the time-domain

$$r[n] = s[n] - h[n]$$

where $h[n]$ is either $h_1[n], h_2[n]$, or $h_3[n]$.

Parameters Estimation

- Pitch: based on an autocorrelation criterion
- Maximum Voiced Frequency: voicing matching criteria
- Amplitudes: Least-Squares
- Noise part: variance and Linear prediction

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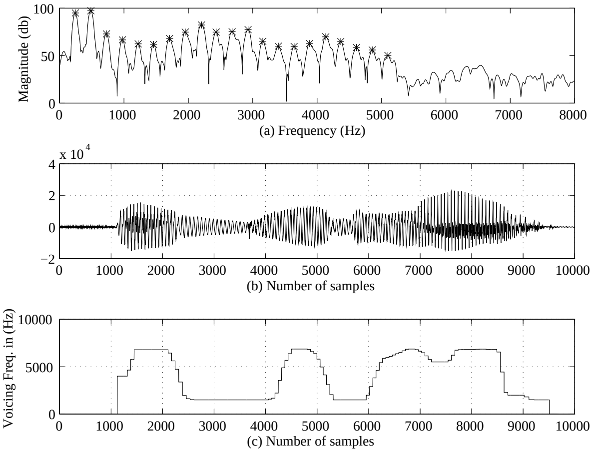
Example of Estimation

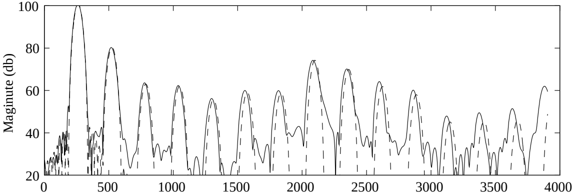


Fundamental frequency refinement

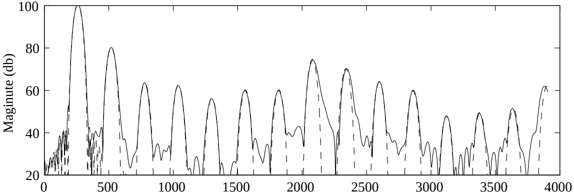
Using the initial f_0 value and the L detected voiced frequencies f_i, then the refined fundamental frequency, $\hat{f}_0$ is defined as the value that minimizes the error:

$$E(\hat{f}_0) = \sum_{i=1}^{L} |f_i - i \cdot \hat{f}_0|^2$$

Refinement frequency example

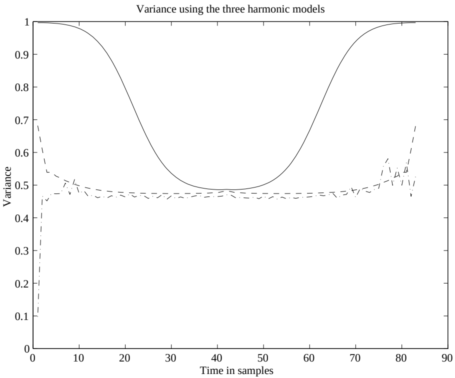


(a) Frequency in Hz



(b) Frequency in Hz

Variance of the residual signal



Synthesis

- Direct time frequency matching
- For the periodic part: Overlap-and-Add, or
  - Linear amplitude interpolation
  - Linear phase interpolation using average pitch value
- For the stochastic (noise) part):
  - Instead of AR coefficients we use reflection coefficients
  - Sample-by-sample filtering of Gaussian noise using normalized lattice filtering
  - Modulation in time with a deterministic function (i.e., triangular)

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Preparing for prosody modifications

For being able to make prosodic modifications (at least pitch and time scale modifications) in the context of HNM, we should

- Associate analysis and synthesis time instants
- Determine a continuous magnitude envelope
- Determine a continuous phase envelope

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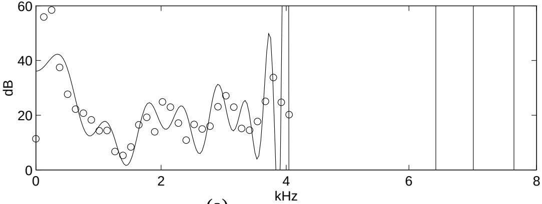
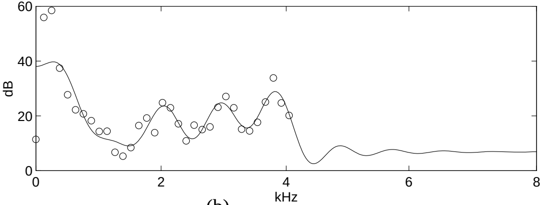
Magnitude: Discrete Cepstrum

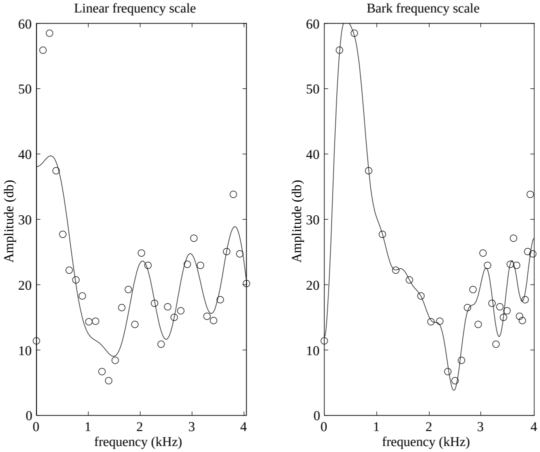


(a)

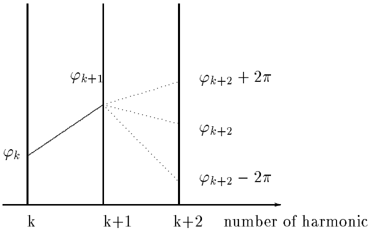


(b)

Bark scaled Disc. Cepstra



Phase envelope estimation



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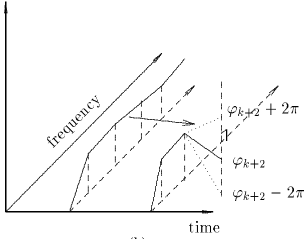
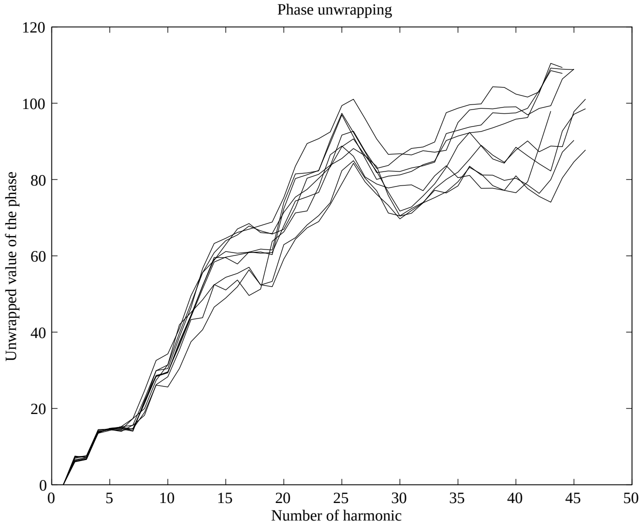
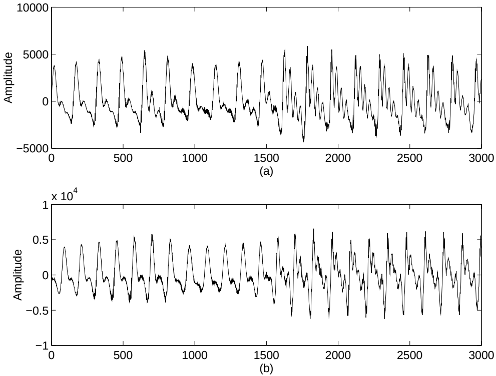


(b)

Example of Phase envelopes



Example of pitch modification



Pitch modification by 1.3

Sound Examples

Original	
Time-scale by 0.7	
Time-scale by 1.6	
Pitch modification by 0.8	
Pitch modification by 1.6	
Original	
Time-varying pitch and time modif.	
Original	
Time-scale by 4	
Time-scale by 6	

Probabilistic classification

- Modeling of the acoustic space of a speaker by a GMM :

$$p(\mathbf{x}) = \sum_{i=1}^{m} \alpha_i N(\mathbf{x}; \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i),$$

- Classification:

$$P(\mathcal{C}_i|\mathbf{x}) = \frac{\alpha_i N(\mathbf{x}; \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)}{\sum_{j=1}^{m} \alpha_j N(\mathbf{x}; \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)}$$

- Estimation using an Expectation-Maximization (EM) algorithm initialized by a standard binary splitting VQ procedure.

Mapping function

- Mapping function [7]:

$$\mathcal{F}(\mathbf{x}_t) = \sum_{i=1}^{m} P(\mathcal{C}_i|\mathbf{x}_t)\left[\boldsymbol{\nu}_i + \boldsymbol{\Gamma}_i \boldsymbol{\Sigma}_i^{-1}(\mathbf{x}_t - \boldsymbol{\mu}_i)\right]$$

- Motivation:

$$E[\mathbf{y}|\mathbf{x} = \mathbf{x}_t] = \nu + \boldsymbol{\Gamma}\boldsymbol{\Sigma}^{-1}(\mathbf{x}_t - \mu)$$

- Estimation of mapping function:

$$\epsilon = \sum_{t=1}^{n} ||\mathbf{y}_t - \mathcal{F}(\mathbf{x}_t)||^2$$

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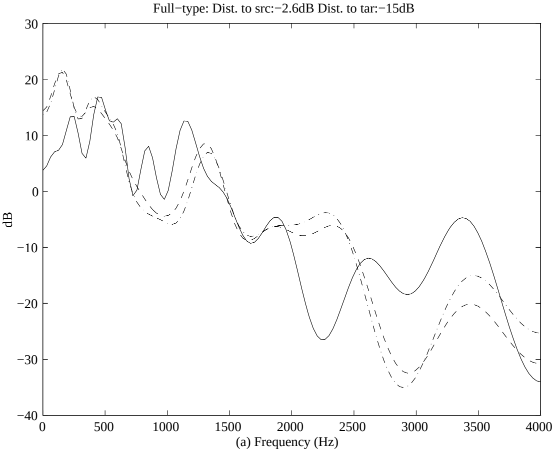
Performance of the mapping function



Results - XAB test

Task: Listeners were asked to select either A or B as being most similar to X.

	PO	16 GMM	64 GMM	64 GMM(2)
Correct answers	18%	83%	88%	97%

Audio examples of Voice Conversion: HNM + GMM

Source	Converted	Target
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D. Griffin and J. Lim, "Multiband-excitation vocoder," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. ASSP-36, pp. 236–243, Fev 1988.

A. Abrantes, J. Marques, and I. Transcoso, "Hybrid sinusoidal modeling of speech without voicing decision," *Eurospeech-91*, pp. 231–234, 1991.

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B.Yegnanarayana, C. d'Alessandro, and V. Darsinos, "An iterative algorithm for decomposition of speech signals into periodic and aperiodic components," vol. 6, no. 1, 1998.

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