CS578 - Speech Signal Processing

Lecture : Quasi-Harmonic Models of Speech

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(based on material from Prof. Stylianou)

Speech Signal Processing Lab
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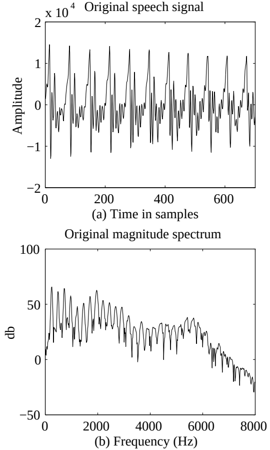
2 November 2022

Outline

Motivation for HNM



Brief overview of HNM

- HNM (Stylianou 1995 [1]) 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 *lower* 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.

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HNM in equations

- Harmonic part:

$$h(t) = \sum_{k=-K(t)}^{K(t)} A_k(t) e^{j2\pi k f_0(t) t}$$

  where $A_k(t)$ and $f_0(t)$ are the instantaneous complex amplitude and real frequency, respectively

- Noise part:

$$n(t) = e(t)\left[v(\tau, t) \star g(t)\right]$$

  where $e(t), v(\tau, t), g(t)$ are a time envelope, an estimation of the PSD (filter), and white gaussian noise, respectively

- Speech:

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

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Estimating Sinusoidal parameters

- Sinusoidal representation for a speech/signal frame:

$$x(t) = \left(\sum_{k=-K}^{K} a_k e^{j2\pi f_k t} \right) w(t)$$

- Parameter estimation methods:
  - FFT-based methods (i.e., QIFFT [Abe et al., 2004-05], [2], [3])
  - Least Squares (LS) method
- Frequency mismatch (eg, $\hat{f}_k := k\hat{f}_0$ in HNM):

$$\hat{f}_k = f_k + \eta_k$$

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Quasi-Harmonic Model, QHM [5]

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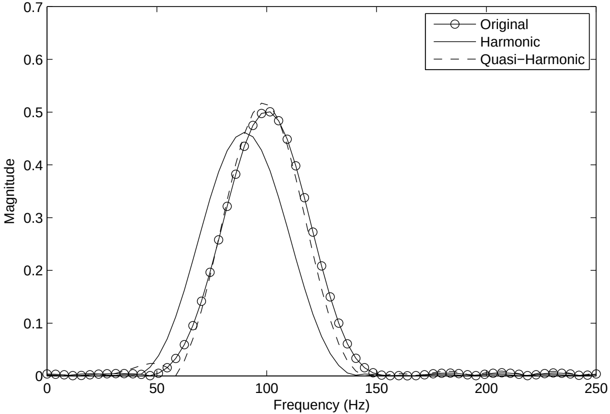
- HM versus QHM in frequency estimation - pure tone @ 100 Hz
- Given frequency for both models: 90 Hz



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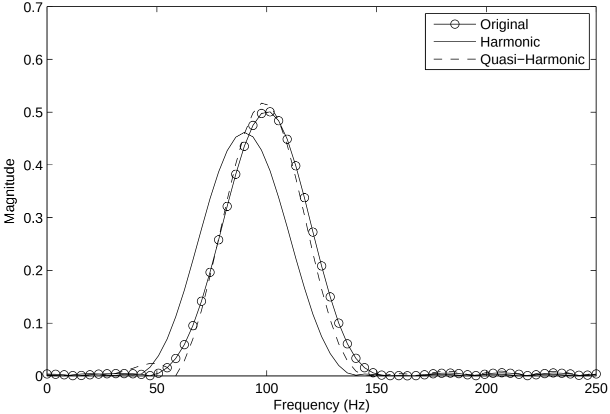

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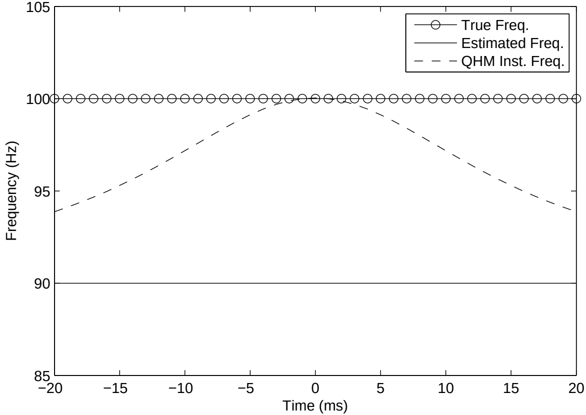

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- Let's discuss a bit on that...

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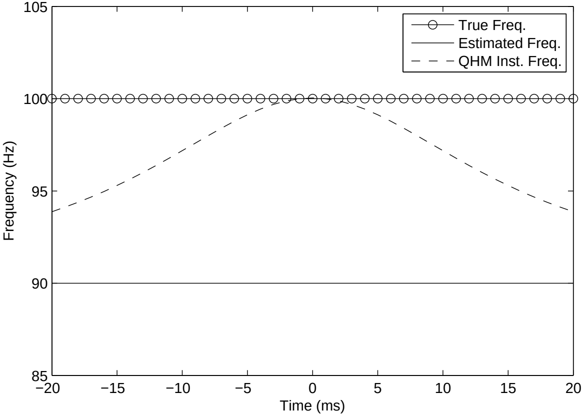

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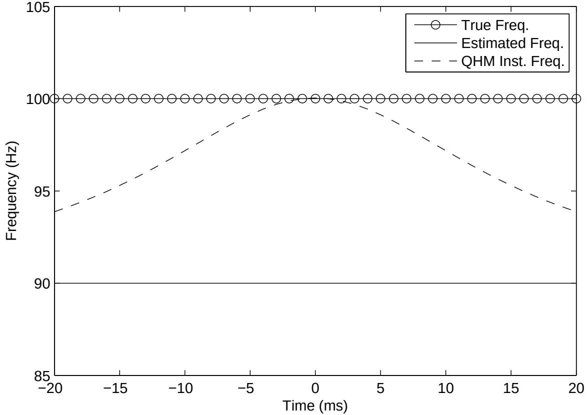

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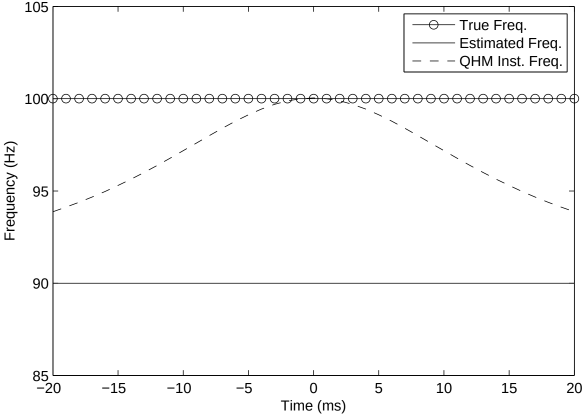

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A few details of QHM

- QHM in the frequency domain:

$$X_k(f) = a_k W(f - \hat{f}_k) + j\frac{b_k}{2\pi} W'(f - \hat{f}_k)$$

- **Decomposition of** b_k: $b_k = \rho_{1,k} a_k + \rho_{2,k} j a_k$
- Then

$$X_k(f) = a_k \left[W(f - \hat{f}_k) - \frac{\rho_{2,k}}{2\pi} W'(f - \hat{f}_k) + j\frac{\rho_{1,k}}{2\pi} W'(f - \hat{f}_k) \right]$$

- and taking into account:

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- Initially, we assumed:

$$x_k(t) = a_k \left[e^{j(2\pi(\hat{f}_k + \eta_k))t} \right] w(t)$$

- in other words, **it is suggested**:

$$\hat{\eta}_k = \rho_{2,k}/2\pi$$

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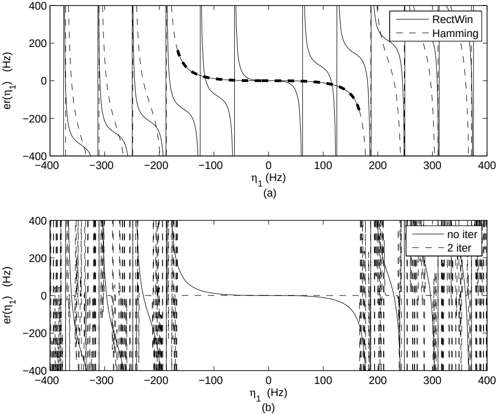
Single Sinusoid



• Iteratively, the bias can be removed when $|\eta| < B/3$, where B is the bandwidth of the squared analysis window.

QHM parameter estimation

- Frame-by-frame analysis:

$$s[n], \;\; n = -N, ..., N$$

- QHM:

$$h[n] = \sum_{k=-K}^{K} (a_k + nb_k) e^{j2\pi f_k n/f_s}, \;\; n = -N, ..., N$$

- Windowed residual error:

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QHM PARAMETER ESTIMATION

- Sum of squared error:

$$
\begin{aligned}
L(\mathbf{a}, \mathbf{b}) &= \sum_{n=-N}^{N} |e[n]|^2 \\
&= \sum_{n=-N}^{N} w[n]^2 \, |s[n] - (E_0(n,:)\mathbf{a} + E_1(n,:)\mathbf{b})|^2 \\
&= \left(\mathbf{s} - [E_0|E_1] \begin{bmatrix} \mathbf{a} \\ \mathbf{b} \end{bmatrix}\right)^H W^2 \left(\mathbf{s} - [E_0|E_1] \begin{bmatrix} \mathbf{a} \\ \mathbf{b} \end{bmatrix}\right)
\end{aligned}
$$

where

- $\mathbf{s} = [s[-N], ..., s[N]]^T \in \mathbb{R}^{2N+1}$
- $\mathbf{a} = [a_{-K}, ..., a_K]^T \in \mathbb{C}^{2K+1}$
- $\mathbf{b} = [b_{-K}, ..., b_K]^T \in \mathbb{C}^{2K+1}$
- $(E_0)_{nk} = e^{j2\pi f_k n/f_s} \in \mathbb{C}^{(2N+1)\times(2K+1)}$
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- Least Squares solution:

$$\begin{bmatrix} \hat{\mathbf{a}} \\ \hat{\mathbf{b}} \end{bmatrix} = \left([E_0|E_1]^H W^2 [E_0|E_1] \right)^{-1} [E_0|E_1]^H W^2 \mathbf{s}$$

- A necessary condition for well-posed estimation is

$$4K + 1 < 2N + 1$$

- Typically, we consider (analysis) window length of 3 periods (with 2 periods being the bare minimum).

QHM parameter estimation

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Outline

ITERATIVE QHM, IQHM [6]

- This frequency updating mechanism provides frequencies which can be used in the model iteratively and result in better parameter estimation (a_k, b_k)
- This iterative parameter estimation is referred to as the *iterative QHM*

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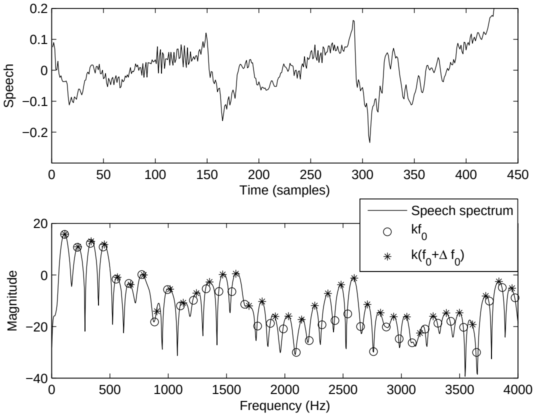
HM versus iQHM in frequency estimation - speech signal:



Robustness against additive noise

- Signal contaminated by noise:

$$y(t) = \sum_{k=1}^{4} a_k e^{j2\pi f_k} + v(t)$$

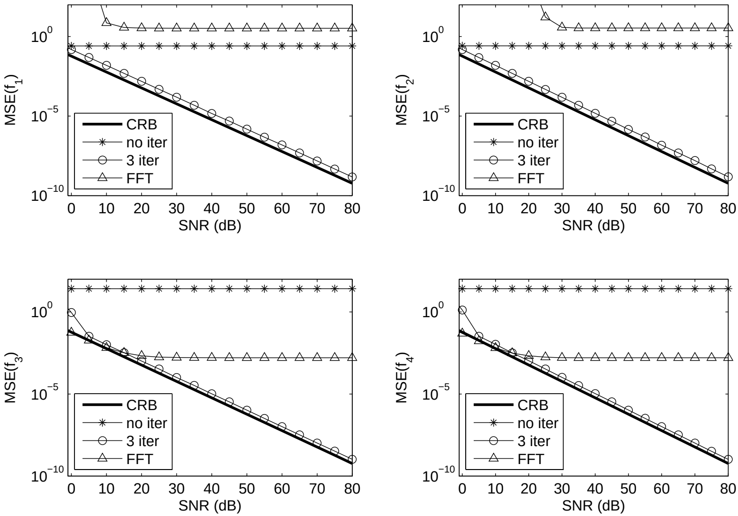
- Mean Squared Error (MSE):

$$MSE\{\hat{f}_k\} = \frac{1}{\mathrm{M}} \sum_{i=1}^{\mathrm{M}} |\hat{f}_k(i) - f_k|^2$$

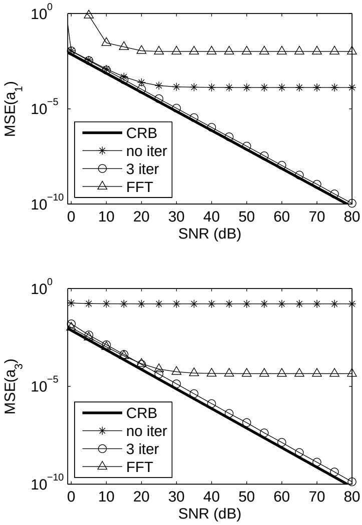
$$MSE\{\hat{a}_k\} = \frac{1}{\mathrm{M}} \sum_{i=1}^{\mathrm{M}} |\hat{a}_k(i) - a_k|^2$$

- Comparison with Cramer-Rao Bounds (CRB) and QIFFT (Abe et al. 2004)
- 10000 Monte Carlo simulations

MSE of frequencies as a function of SNR.



MSE OF AMPLITUDES AS A FUNCTION OF SNR.



Notes on QHM

- QHM has been shown to be closely related to:
  - Gauss-Newton frequency estimation method
  - Reassigned Spectrogram
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High resolution AM-FM decomposition

- AM-FM signal

$$y(t) = \sum_{k=1}^{K(t)} a_k(t) cos(\phi_k(t)),$$

- Taylor series expansion of the instantaneous phase of kth component:

$$\phi_k(t) = 2\pi\zeta_k t + \sum_{i=0}^{\infty} \phi_{k,i} \frac{t^i}{i!}$$

- Instantaneous frequency of the kth component at $t = 0$:

$$\nu_k(0) = \zeta_k + \frac{\phi_{k,1}}{2\pi}$$

- ... and previously we had:

$$F_k(0) = f_k + \frac{\rho_{2,k}}{2\pi}$$

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From QHM to Adaptive QHM, aQHM [7]

- QHM (**stationarity assumption**):

$$x(t) = \left(\sum_{k=-K}^{K} (a_k + tb_k) e^{2\pi j f_k t} \right) w(t)$$

- Adaptive QHM (aQHM):

$$x(t) = \left(\sum_{k=-K}^{K} (a_k + tb_k) e^{j\tilde{\phi}_k(t)} \right) w(t)$$

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$$\tilde{\phi}_k(t) = 2\pi \int_0^t f_k(s) ds + \varphi, \;\; t \in [0, T]$$

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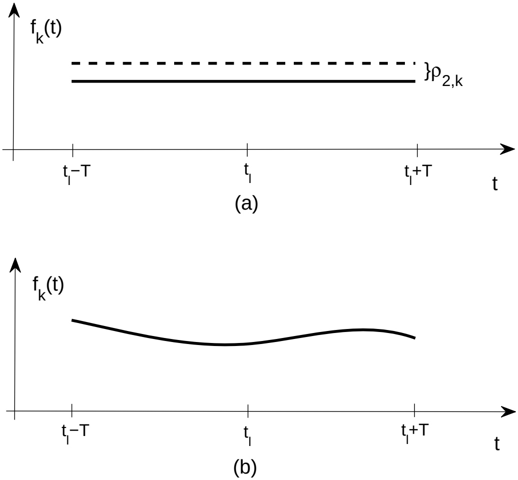
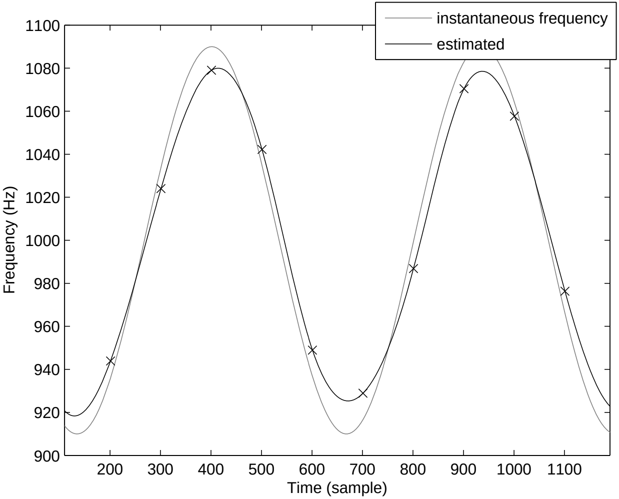
From QHM to aQHM; Graphically



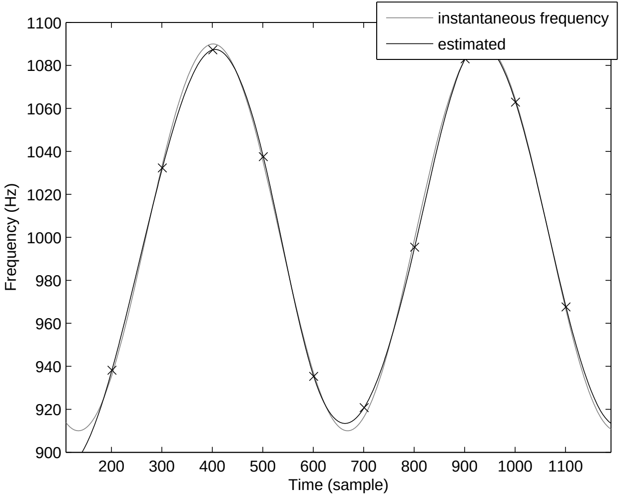
aQHM, in practice

- One sample: no interpolation between estimations
- Higher rates (i.e., 5ms, 10ms): Interpolation between estimates is required:
  - Amplitudes are linearly interpolated
  - Frequencies are interpolated with splines
  - Phases are interpolated by integration of instantaneous frequency

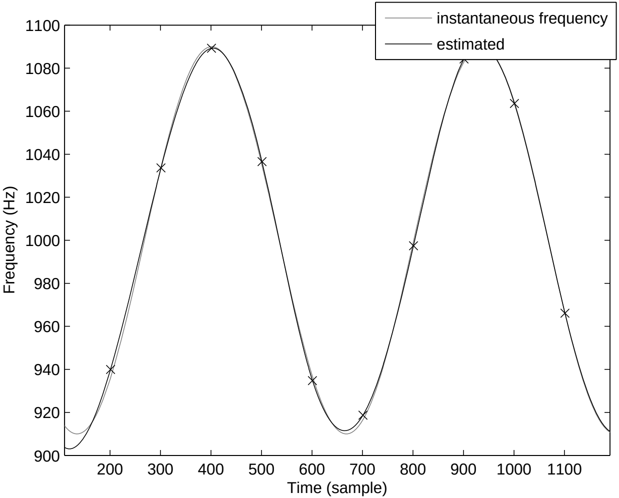
Example of estimation in aQHM: no iteration (QHM)



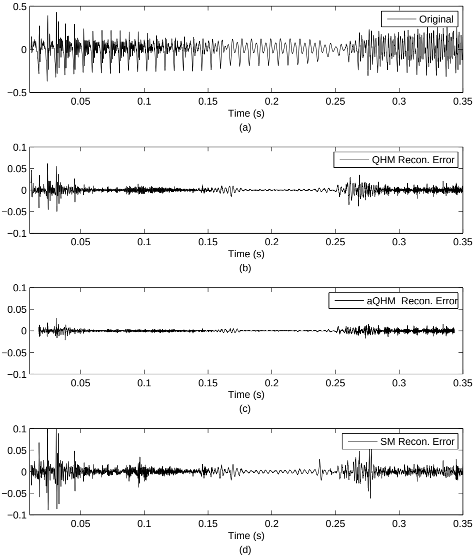
Example of estimation in aQHM: one iteration



Example of estimation in aQHM: two iterations



Reconstruction errors with QHM, aQHM, SM



Outline

Extended aQHM

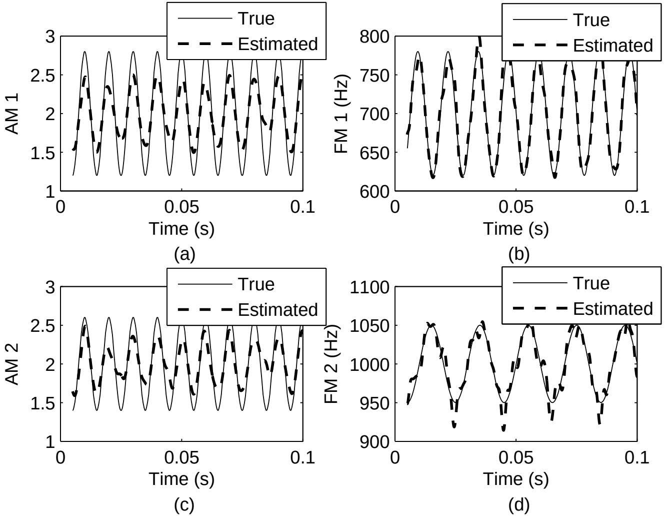
- Recall aQHM:

$$x(t) = \sum_{k=-K}^{K} (a_k + tb_k) e^{j\tilde{\phi}_k(t)}$$

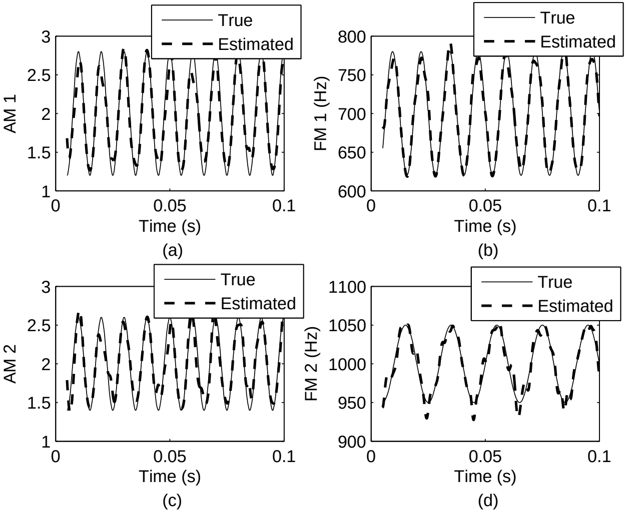
- Extended aQHM:

$$x(t) = \sum_{k=-K}^{K} (a_k + tb_k) \tilde{\alpha}(t) e^{j\tilde{\phi}_k(t)}$$

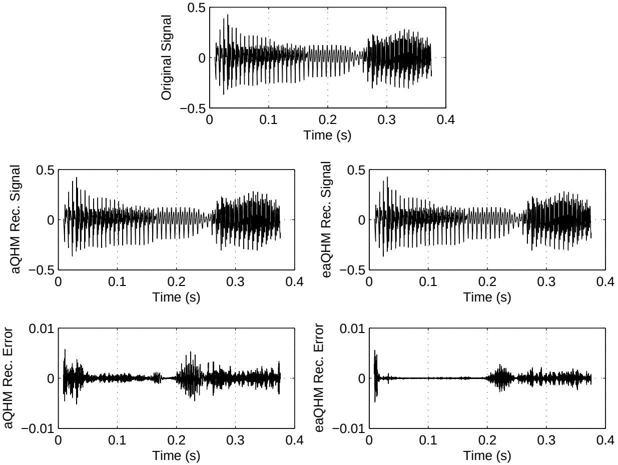
AM-FM modeling: aQHM



AM-FM modeling: extended aQHM



Comparing Adaptive Models



Outline

THANK YOU

for your attention

Outline

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