CS578- Speech Signal Processing

Lecture 6: Adaptive Sinusoidal Models

Yannis Stylianou

University of Crete, Computer Science Dept., Multimedia Informatics Lab
yannis@csd.uoc.gr

Univ. of Crete

Outline

Sinusoidal Model

- Sinusoidal Model:

$$x(t) = \sum_{k=-K}^{K} \gamma_k e^{j2\pi f_k t}$$

- Special case, Harmonic Model:

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

- Estimation of parameters (Linear approach):

$$\gamma = \mathcal{F}_{f_k} \mathbf{s}$$

- Model Evaluation, Mean-Squared Error (MSE):

$$\epsilon = \int_{w} |s(t) - x(t)|^2 \, dt$$

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Towards Adaptive Sinusoidal Models

Estimating Sinusoidal parameters

- Sinusoidal representation for a speech/signal frame:

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

- Methods:
  - FFT-based methods (i.e., QIFFT [Abe et al., 2004-05, [1] [2]])
  - Subspace methods
  - Least Squares (LS) method
- Frequency mismatch:

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

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Quasi-Harmonic Model, QHM [5]

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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

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

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- **Approximation of** the *kth* component of QHM

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

- Back to the time-domain:

$$x_k(t) \approx a_k \left[e^{j(2\pi \hat{f}_k + \rho_{2,k})t} + \rho_{1,k} t e^{j2\pi \hat{f}_k t} \right] w(t)$$

- 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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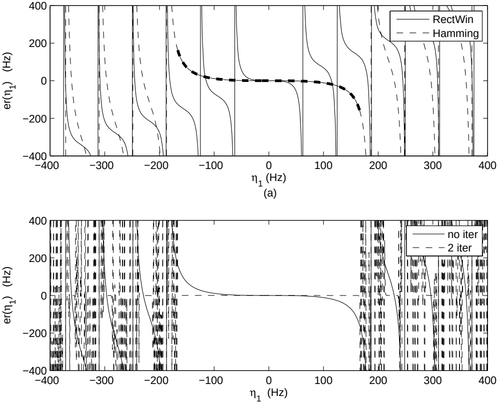
Single Sinusoid



(a)

(b)

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

Robustness against additive noise

- Signal contaminated by noise:

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

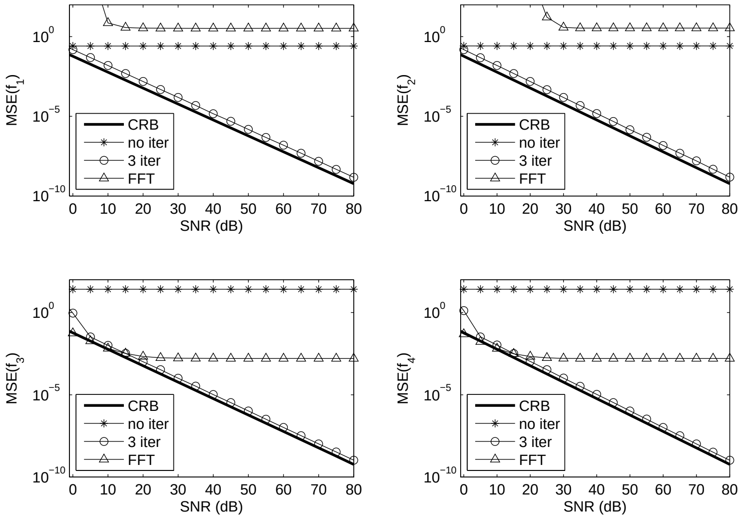
- Mean Squared Error (MSE):

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

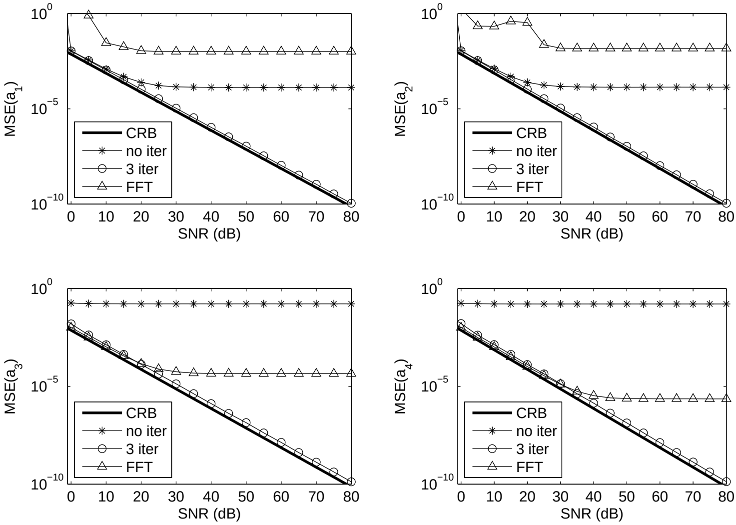
$$MSE\{\hat{a}_k\} = \frac{1}{\mathrm{M}} \sum_{i=1}^{\mathrm{M}} |\hat{a}_k(i) - a_k|^2$$

- 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
- AM-FM decomposition

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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 [6]

- 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):

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

where

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

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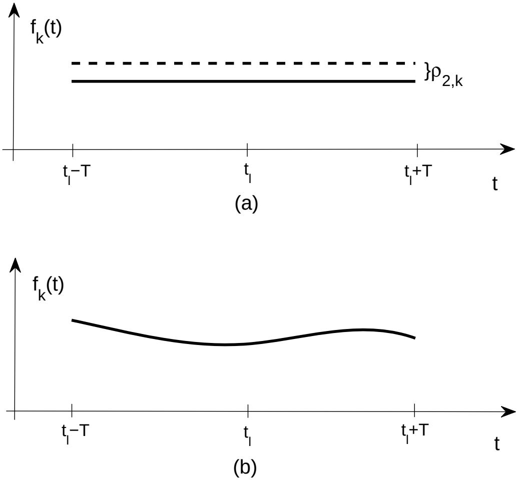
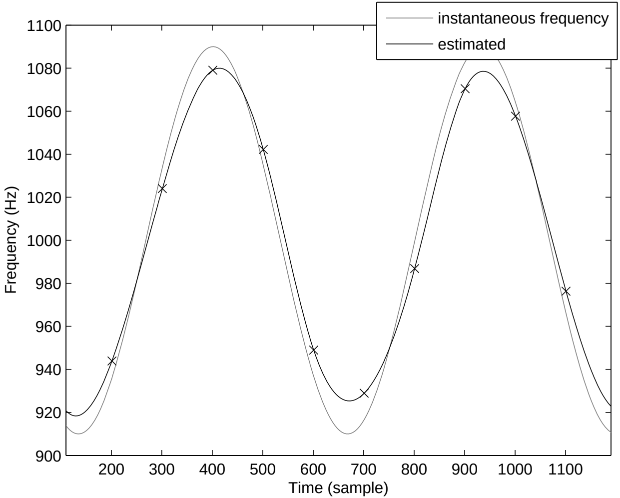
From QHM to aQHM; Graphically



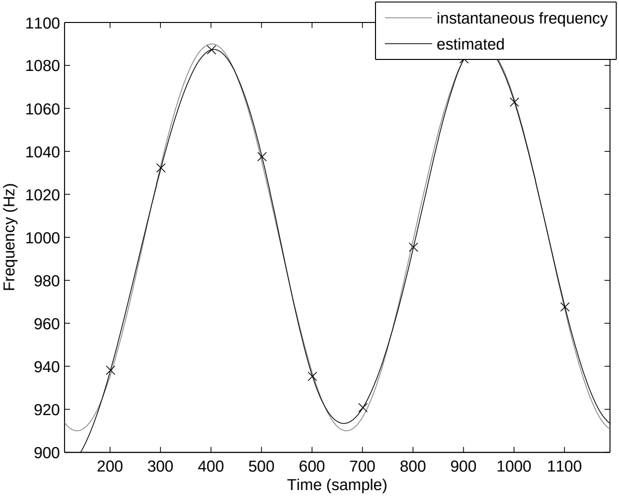
aQHM, in practice

- 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

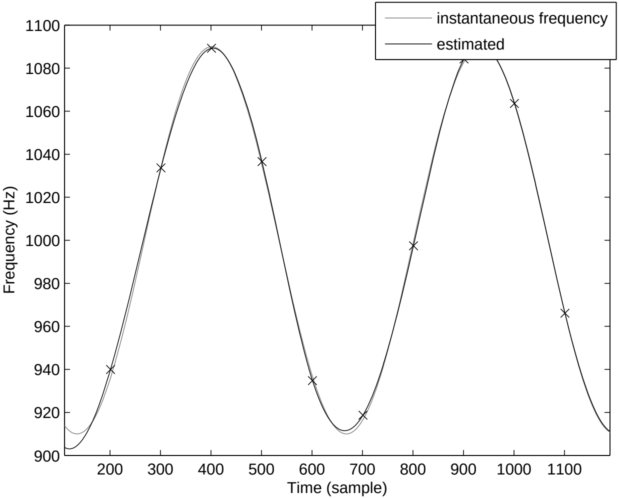
Example of estimation in aQHM: no iteration (QHM)



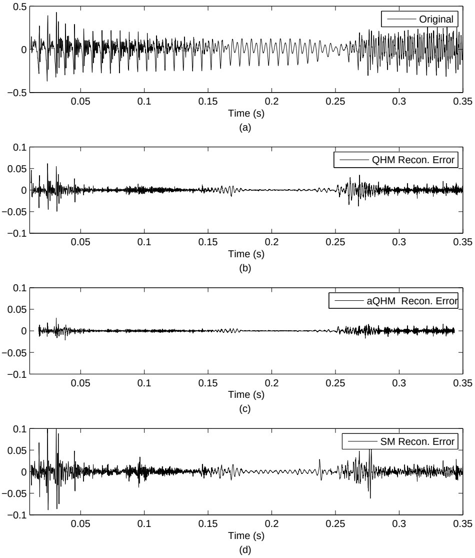
Example of estimation in aQHM: one iteration



Example of estimation in aQHM: two iterations



Reconstruction errors with QHM, aQHM, SM



Outline

Extended aQHM

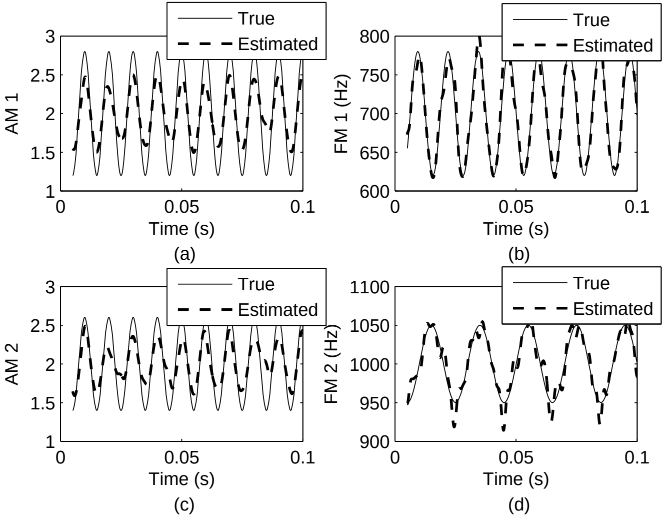
- Recall aQHM:

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

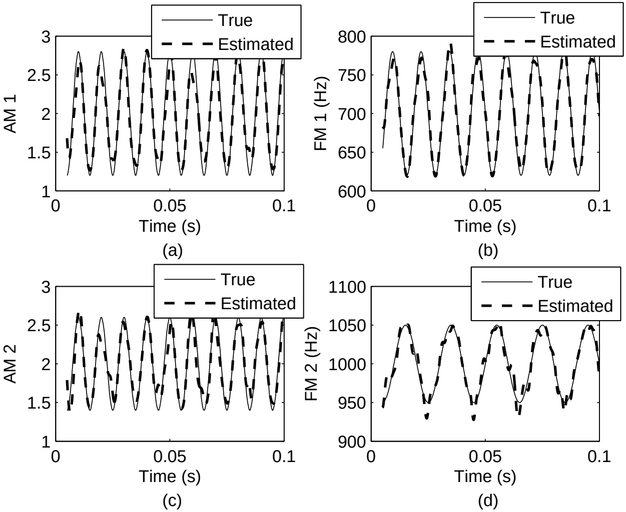
- Extended aQHM:

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

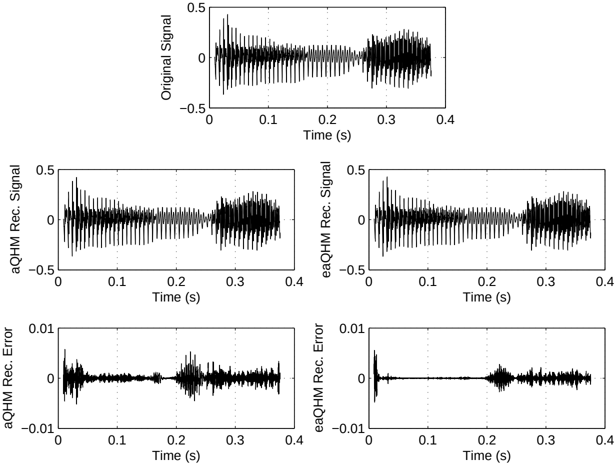
AM-FM modeling: aQHM



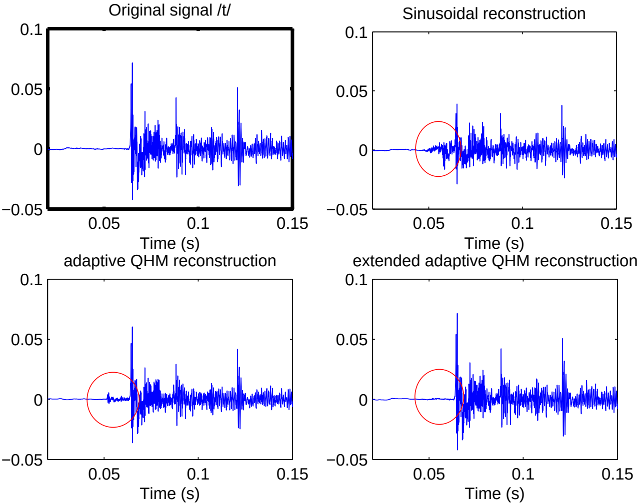
AM-FM modeling: extended aQHM



Comparing Adaptive Models



Stop modeling



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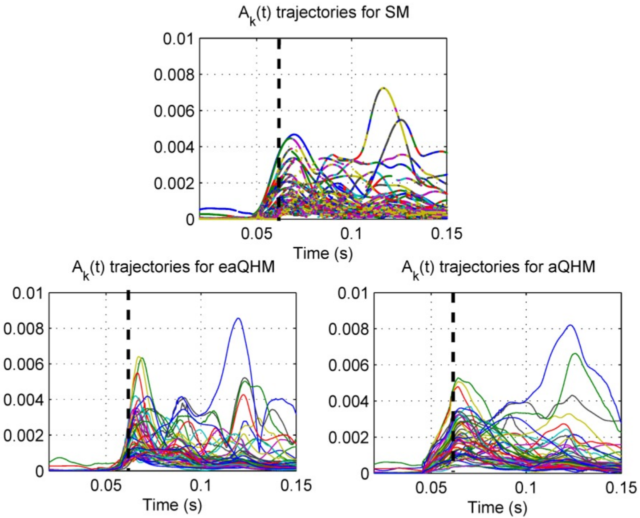
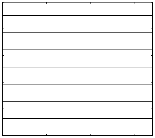


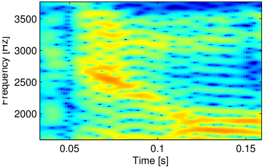
Time-Frequency Representations

DFT $s(t) = \sum_{k=0}^{K} a_k \cdot e^{j\phi_k(t)}$

$\phi_k(t) = k \cdot (2\pi/K) \cdot t$

Constant frequency basis

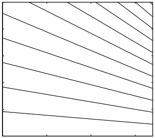


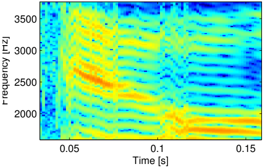


FChT[1] $s(t) = \sum_{k=0}^{K} a_k \cdot e^{j\phi_k(t)}$

$\phi_k(t) = k \cdot (2\pi/K + \alpha \cdot t) \cdot$

Linear frequency basis



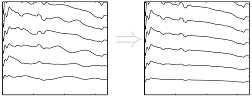


[1] M. Kepesi and L. Weruaga, *Adaptive Chirp-based time-frequency analysis of speech signals*, Speech communication, 2006.

Ideas

1) From FChT, harmonics exist in high frequencies
   - ⇒ Use a full-band representation

2) Quasi-harmonicity can be useful for analysis but maybe not necessary for encoding/decoding
   - ⇒ Use the strict harmonicity and keep the adaptivity



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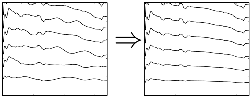
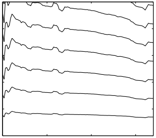


aQHNM$\Rightarrow$aHM

The Adaptive Harmonic Model (aHM)

aHM $s(t) = \sum_{k=-K}^{K} a_k(t) \cdot e^{j\phi_k(t)}$

$$\phi_k(t) = k \cdot \frac{2\pi}{f_s} \int_0^t f_0(\tau) d\tau$$



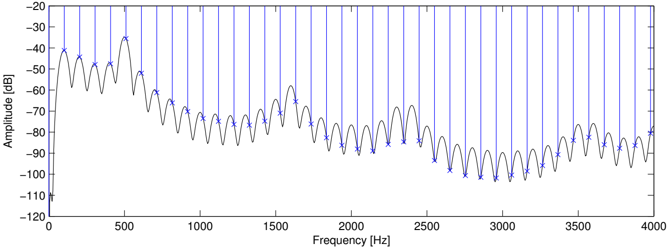
$a_k(t)$ Amplitude and phase (complex-valued function)
Interpolated from $a_k^{t_i}$ at time t_i

$f_0(t)$ Fundamental frequency
Interpolated from $f_0^{t_i}$ at time t_i

Parameters at a time t_i: $\{f_0^{t_i}, a_k^{t_i}\}$ $\quad k \in \{0, ..., K_i\}$

The problem of estimation for full-band representation

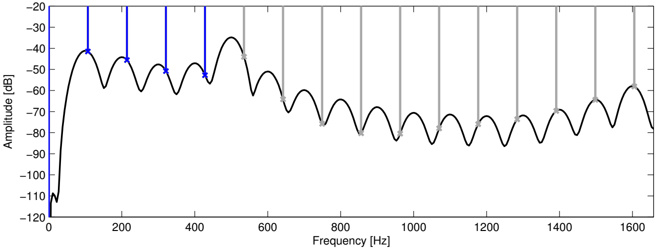
A small f_0 error propagates by multiplication: $f_k = k \cdot f_0$



Question How to estimate harmonics up to Nyquist ?

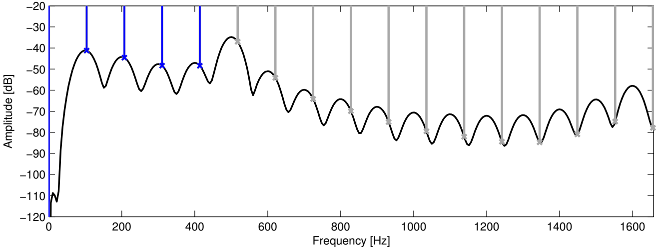
The Adaptive Iterative Refinement (AIR)

Assume first the f_0 error is small for low harmonics



The Adaptive Iterative Refinement (AIR)

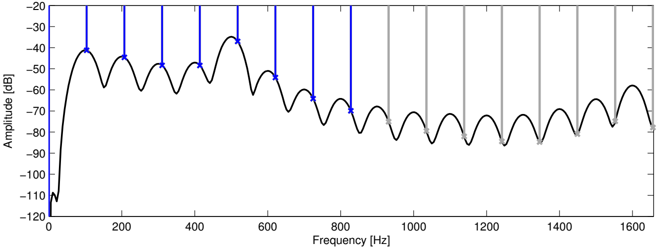
Then the frequency correction mechanism of QHM[1] can be used



[1] Y. Pantazis, O. Rosec and Y. Stylianou, *Iterative Estimation of Sinusoidal Signal Parameters*, IEEE Signal Processing Letters, 2010.

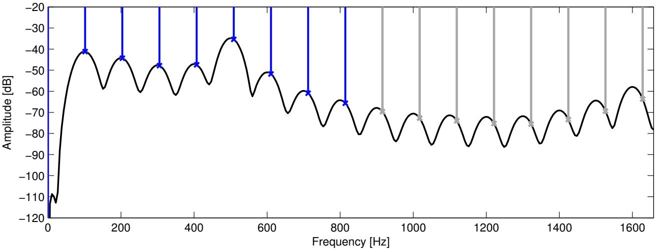
The Adaptive Iterative Refinement (AIR)

We can therefore increase the harmonic level



The Adaptive Iterative Refinement (AIR)

Correct the frequencies



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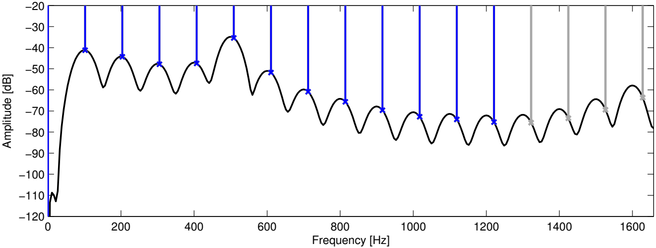

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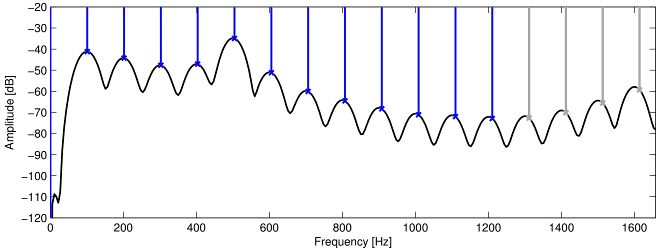

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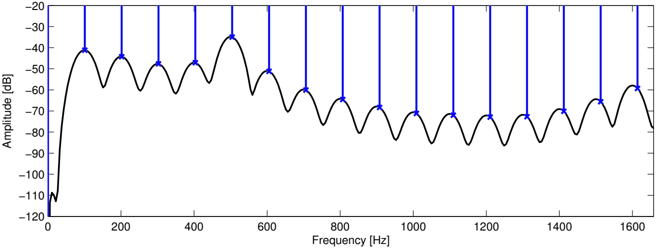

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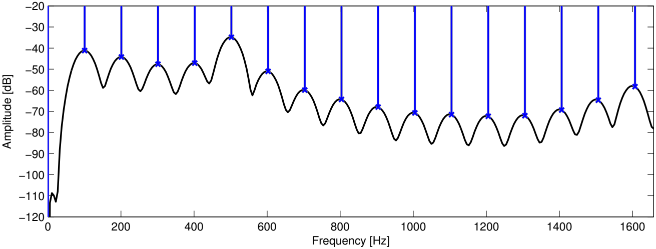

Key papers to read

- Y. Pantazis, O. Rosec, and Y. Stylianou: *Adaptive AM-FM Signal Decomposition with Application to Speech Analysis* IEEE TASLP, Vol.19, No.2, Feb 2011, pp 290-300.
- Y. Pantazis, O. Rosec, and Y. Stylianou: *Iterative Estimation of Sinusoidal Signal Parameters*. IEEE SPL, Vol.17, No.5, May 2010, pp. 461-464
- P. Babu and P. Stoica: *Comments on Iterative Estimation of Sinusoidal Signal Parameters.* Comments on IEEE SPL, pp.1022-1023, Vol.17, No.12, Dec 2010
- Y. Pantazis, O. Rosec, and Y. Stylianou: *Reply to "Comments on 'Iterative Estimation of Sinusoidal Signal Parameters' "* IEEE SPL, pp. 1024-1026, Vol.17, No.12, Dec 2010
- G. Degottex and Y. Stylianou: *Analysis and Synthesis of Speech using an Adaptive Full-band Harmonic Model* IEEE TASLP, Vol.21, Issue 10, pp 2085-2095, 2013

Outline

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- High quality pitch scale modification
- Within glottal cycle formant tracking and modifications towards voice conversion
- Free pre-echo effect in time scaling
- Emotion detection and control

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Acknowledgments

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THANK YOU

for your attention

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M. Abe and J. S. III, “CQIFFT: Correcting Bias in a Sinusoidal Parameter Estimator based on Quadratic Interpolation of FFT Magnitude Peaks,” Tech. Rep. STAN-M-117, Stanford University, California, Oct 2004.

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Y. Pantazis, O. Rosec, and Y. Stylianou, “On the Properties of a Time-Varying Quasi-Harmonic Model of Speech,” (Brisbane), Sep 2008.

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Y. Pantazis, O. Rosec, and Y. Stylianou, “Adaptive AMFM signal decomposition with application to speech analysis,” *IEEE Trans. on Audio, Speech, and Language Processing*, vol. 19, pp. 290–300, 2011.