**ΕΛΛΗΝΙΚΗ ΔΗΜΟΚΡΑΤΙΑ**
**ΠΑΝΕΠΙΣΤΗΜΙΟ ΚΡΗΤΗΣ**

# Ψηφιακή Επεξεργασία Φωνής

**Διάλεξη:** Προσαρμόσιμα Ημιτονοειδή Μοντέλα

Παρουσίαση: Γιώργος Καφεντζής

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Τμήμα Επιστήμης Υπολογιστών

# Adaptive Sinusoidal Models

## A tutorial

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# Outline

# Introduction

- Sinusoidal modeling of speech

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- Essential assumption: **local stationarity!**

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- Essential assumption: **local stationarity!**
  - Speech is considered stationary in short time intervals
  - (it is not, but it is a convenient assumption :-) )

# Sinusoidal modeling - Quatieri, McAulay, 1986

- Each frame is modeled as a sum of sinusoids:

$$s(t) = \sum_{k=-K}^{K} a_k e^{j(2\pi f_k t)}$$

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  - Estimation of the sinusoidal parameters: FFT + peak picking
  - Various improvements (e.g. quadratic interpolation)
- Highlight: **no distinction between voiced and unvoiced frames**

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Signal reconstruction:

- Overlap Add method: $\hat{s}(t) = \sum_{k=-K}^{K} \hat{a}_k e^{j2\pi \hat{f}_k t}$

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  - **Speech is not purely harmonic ($\mathbf{f_k \approx kf_0}$)**
    - ...this last observation is the motivation for the following model...

# Outline

# Quasi-Harmonic model - Pantazis, Stylianou, Rosec, 2007-2010

- $s_d(t) = \sum_{k=-K}^{K} (a_k + tb_k) e^{j2\pi \hat{f}_k t} w(t)$

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- $w(t)$ is the analysis window
- Again: Least Squares method for finding amplitudes
- Window length $\approx$ 3 pitch periods
- Reconstruction:

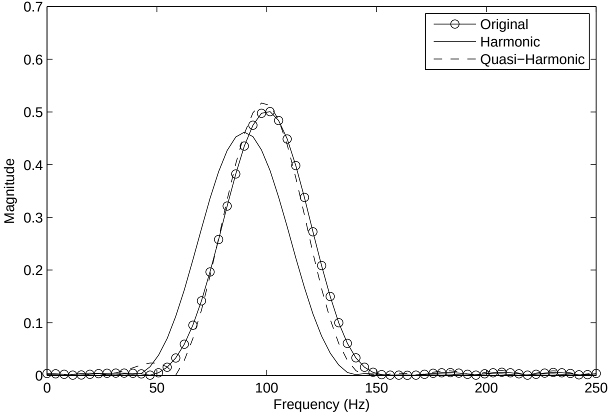
$$\hat{s}_d(t) = \sum_{k=-K}^{K} (\hat{a}_k + t\hat{b}_k) e^{j2\pi \hat{f}_k t} \tag{1}$$

# Quasi-Harmonic model

- HM versus QHM in frequency estimation - pure tone @ 100 Hz

# Quasi-Harmonic model

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



# Quasi-Harmonic model

Time domain properties:

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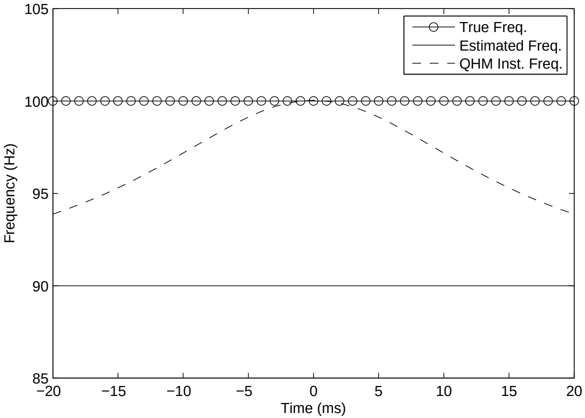
- where $x^R, x^I$ denote the real and imaginary part of $x$

# Quasi-Harmonic model

HM vs QHM on frequency tracks - pure tone @ 100 Hz:




- Highlight: **frequency correction mechanism**

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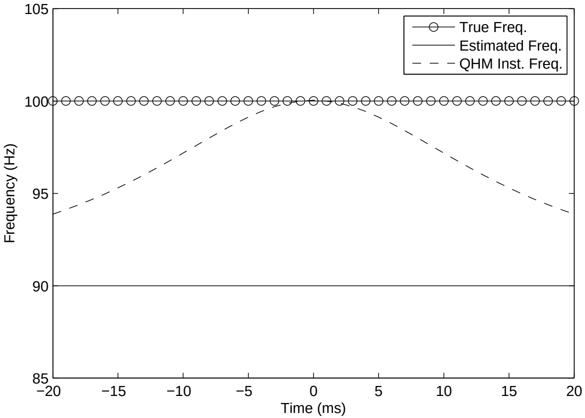


- Highlight: **frequency correction mechanism**
  - Let's discuss a bit on that...

# Frequency mismatch correction

Frequency domain view:

- Fourier Transform of the model:

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- Projecting $b_k$ to $a_k$:

$$b_k = \rho_{1,k} a_k + \rho_{2,k} j a_k \quad (3)$$

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- Then,

$$X_k(f) = a_k \left[ W(f - \hat{f}_k) - \frac{\rho_{2,k}}{2\pi} W'(f - \hat{f}_k) + j\frac{\rho_{1,k}}{2\pi} W'(f - \hat{f}_k) \right] \quad (4)$$

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  - If the value of term $W''(f)$ at $f_k$ is small, then for small values of $\rho_{2,k}$, it is:
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- So,

$$X_k(f) \approx a_k\left[W(f-\hat{f}_k-\frac{\rho_{2,k}}{2\pi})+j\frac{\rho_{1,k}}{2\pi}W'(f-\hat{f}_k)\right] \quad (7)$$

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- $$x_k(t) \approx a_k \left[ e^{j(2\pi \hat{f}_k + \rho_{2,k})t} + \rho_{1,k} t e^{j2\pi \hat{f}_k t} \right] w(t) \qquad (8)$$

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- Then, $\rho_{2,k}/2\pi$ can be an estimator of the frequency error $\eta_k$:

$$\hat{\eta}_k = \rho_{2,k}/2\pi = \frac{1}{2\pi} \frac{a_k^R b_k^I - a_k^I b_k^R}{|a_k|^2} \tag{9}$$

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- In other words, QHM suggests a frequency correction to the input frequencies $\hat{f}_k$ (or a frequency estimator). This suggestion is however conditional on the magnitude of $\rho_{2,k}$ and the value of term $W''(f)$ at $f_k$

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- $$x_k(t) \approx a_k \left[ e^{j(2\pi \hat{f}_k + \rho_{2,k})t} + \rho_{1,k} t e^{j2\pi \hat{f}_k t} \right] w(t) \qquad (8)$$
- Then, $\rho_{2,k}/2\pi$ can be an estimator of the frequency error $\eta_k$:

$$\hat{\eta}_k = \rho_{2,k}/2\pi = \frac{1}{2\pi} \frac{a_k^R b_k^I - a_k^I b_k^R}{|a_k|^2} \qquad (9)$$

- In other words, QHM suggests a frequency correction to the input frequencies $\hat{f}_k$ (or a frequency estimator). This suggestion is however conditional on the magnitude of $\rho_{2,k}$ and the value of term $W''(f)$ at $f_k$
- Also, the correction term depends on the window mainlobe width

# Outline

# iterative QHM - Pantazis, Stylianou, Rosec, 2007-2010

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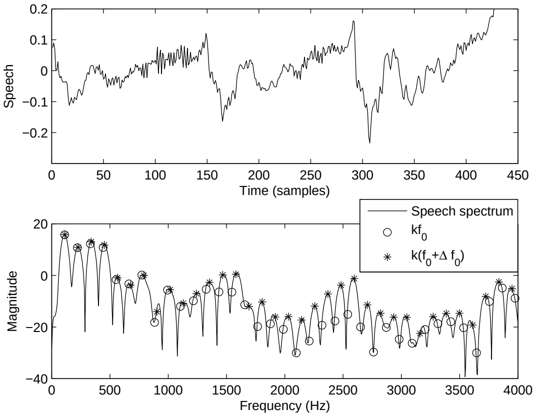
- This iterative parameter estimation is referred to as the *iterative QHM*

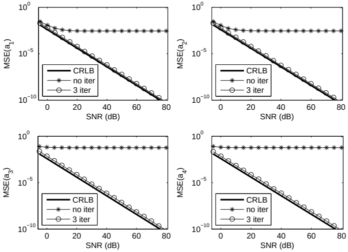
# iterative QHM

HM versus iQHM in frequency estimation - speech signal:

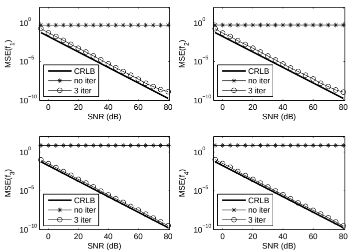


# iterative QHM

Noise robustness:




(a) MSE for amplitudes




(b) MSE for frequencies

Figure: Noise Robustness

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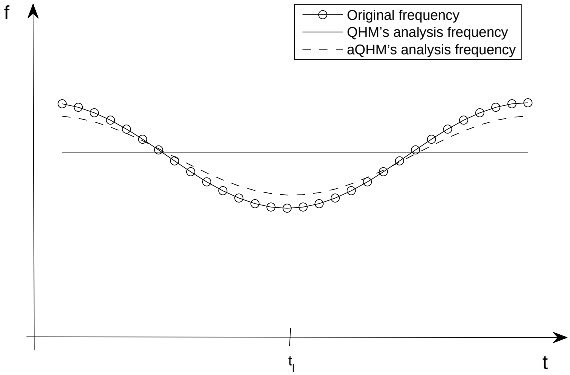
- Adaptation algorithm can be found in [5]

# Adaptive Quasi-Harmonic model

QHM vs aQHM:



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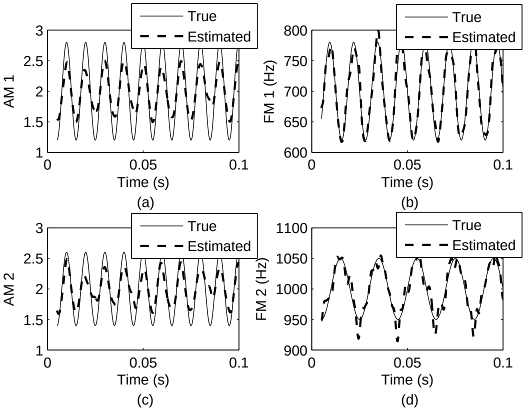
# Adaptive Quasi-Harmonic model

Synthetic signal:



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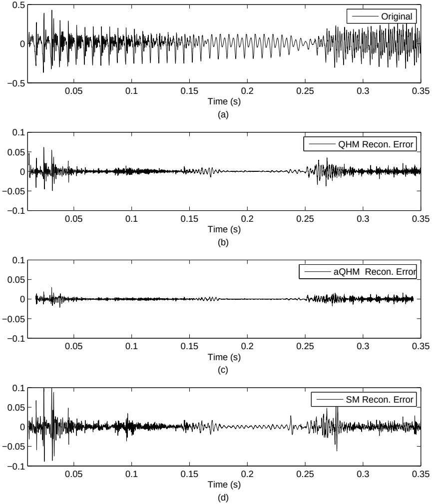

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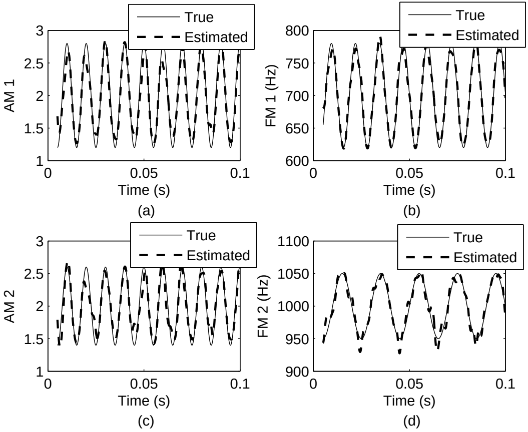

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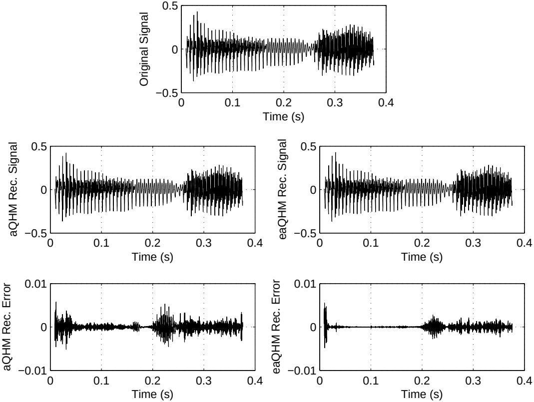
| MAE scores and SRER | | | | | | |
|---|---|---|---|---|---|---|
| SNR | Model | $a_1(t)$ | $a_2(t)$ | $F_1(t)$ | $F_2(t)$ | SRER(dB) |
| $\infty$ | aQHM | 0.2380 | 0.1842 | 7.6105 | 9.1731 | 22.6 |
| | eaQHM | **0.0889** | **0.0949** | **5.9217** | **7.0505** | **42.0** |
| 10 dB | aQHM | 0.2317 | 0.1860 | 8.6071 | 9.0302 | 10.7 |
| | eaQHM | **0.1490** | **0.1476** | **8.0513** | **8.1022** | **10.9** |

Table: MAE scores and SRER for aQHM and eaQHM for $10^4$ Monte Carlo simulations.

# Extended Adaptive Quasi-Harmonic model

Real Signal:



# Adaptation algorithm for eaQHM

- Let $\hat{A}_k(t_l), \hat{f}_k(t_l), \hat{\phi}_k(t_l)$ denote the inst. amplitude, frequency, and phase at time instant $t_l$ of the $k^{th}$ component, with $l = 1, \cdots, L$, where $L$ is the number of frames:
- Initialization: (QHM)
  1) $\hat{f}_k^0(t_l) = \hat{f}_k^0(t_{l-1}) + \rho_{2,k}^0/2\pi$
  2) $\hat{A}_k^0(t_l) = |a_k^0|, \ \hat{\phi}_k^0(t_l) = \angle a_k^0$
  3) $\hat{f}_k^0(t_{l+1}) = \hat{f}_k^0(t_l)$
- FOR adaptation $i = 1, 2, \cdots$
  FOR frame $l = 1, 2, \cdots, L$
  1. Compute $a_k^l, b_k^l$ using $\hat{\phi}_k^{i-1}(t)$ and (11)
  2. Update $\hat{f}_k^i(t_l)$ using **(9)**
  3. Compute $\hat{A}_k^i(t_l)$ and $\hat{\phi}_k^i(t_l)$

  END
  4. Interpolation of the parameters $\{\hat{A}_k^i(t), \hat{f}_k^i(t), \hat{\phi}_k^i(t)\}$

  END

# Extended Adaptive Quasi-Harmonic model

Analysis-Synthesis System

- Seperate speech into two parts: deterministic and stochastic

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# Extended Adaptive Quasi-Harmonic model

Analysis-Synthesis System

- Seperate speech into two parts: deterministic and stochastic
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- Stochastic part: time and frequency modulated (energy-based envelope and AR modeling)

# Extended Adaptive Quasi-Harmonic model

Analysis-Synthesis System

- Seperate speech into two parts: deterministic and stochastic
- Deterministic part: a sum of non-stationary sinusoids (ea/aQHM)
- Stochastic part: time and frequency modulated (energy-based envelope and AR modeling)
- Very high quality of speech signal reconstruction

# Outline

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# Time for Questions!

Thank you for your attention!
Any questions? :-)

# Τέλος Ενότητας

Με τη συγχρηματοδότηση της Ελλάδας και της Ευρωπαϊκής Ένωσης

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