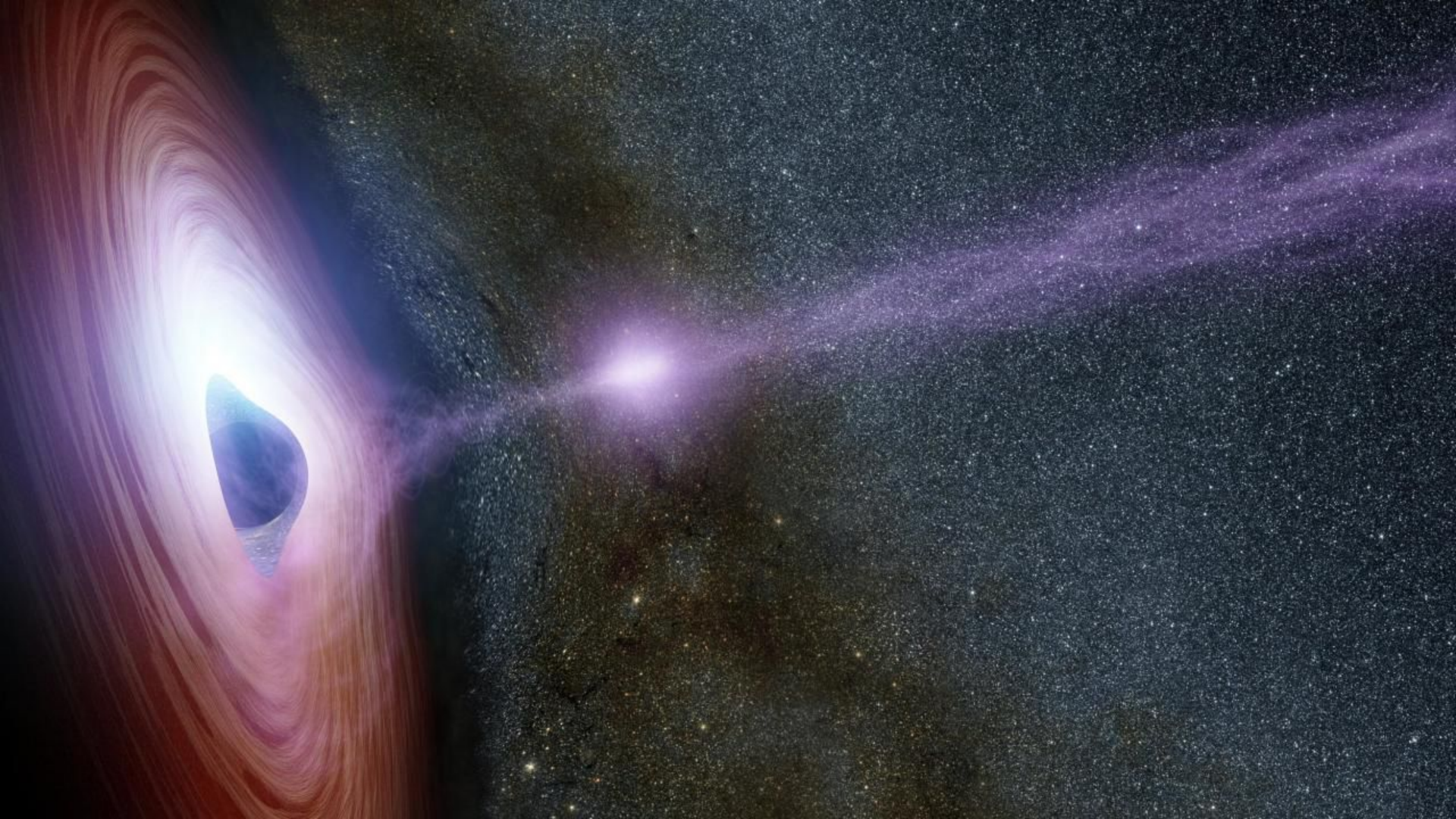
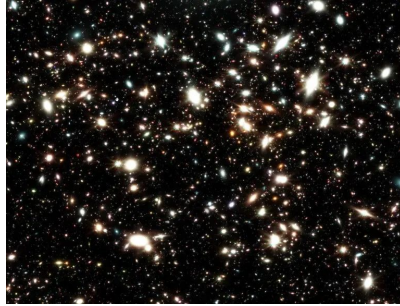


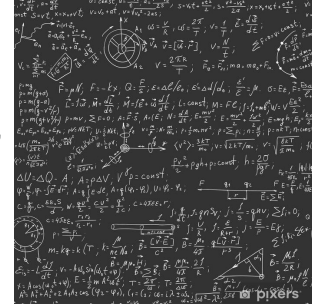
The Hilbert-Huang Transform

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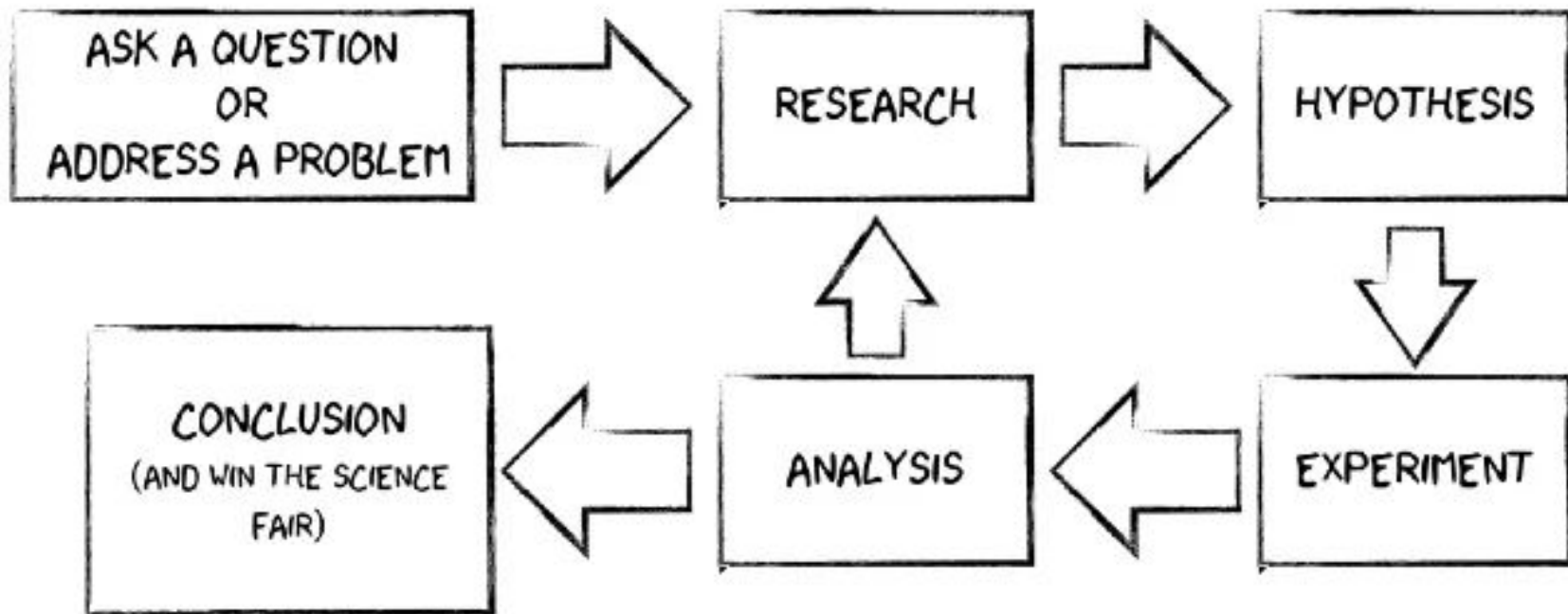


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THE SCIENTIFIC METHOD



What's up?

The need for an adaptive basis

- Traditionally, assume stationary and/or linearity
 - Real world?
- A priori basis
 - Fourier transform: trigonometric functions
 - Convolution computation
- A posteriori basis
 - Adaptive — let the data speak for themselves!
 - Arbitrary selection of basis \leftrightarrow representation of a physical process

The Hilbert-Huang Transform (HHT)


- Designed for linear and nonstationary data
- HHT = Empirical Mode Decomposition (EMD) + Hilbert Transform
- Data $\xrightarrow{\text{EMD}}$ Intrinsic Mode Functions (IMFs)
- Physically meaningful instantaneous frequency and amplitude

The Hilbert Spectral Analysis

- To deal with nonstationary/nonlinearity, allow for instantaneous frequency and amplitude
- For the time series $x(t)$, define the Hilbert transform as

$$y(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{x}{(t - \tau)} d\tau,$$

- Define a complex signal

$$z(t) = x(t) + iy(t) = a(t)e^{i\theta(t)}$$

$$\theta(t) = \tan^{-1}\left(\frac{y}{x}\right)$$
$$a(t) = (x^2 + y^2)^{1/2}$$

The Hilbert Spectral Analysis

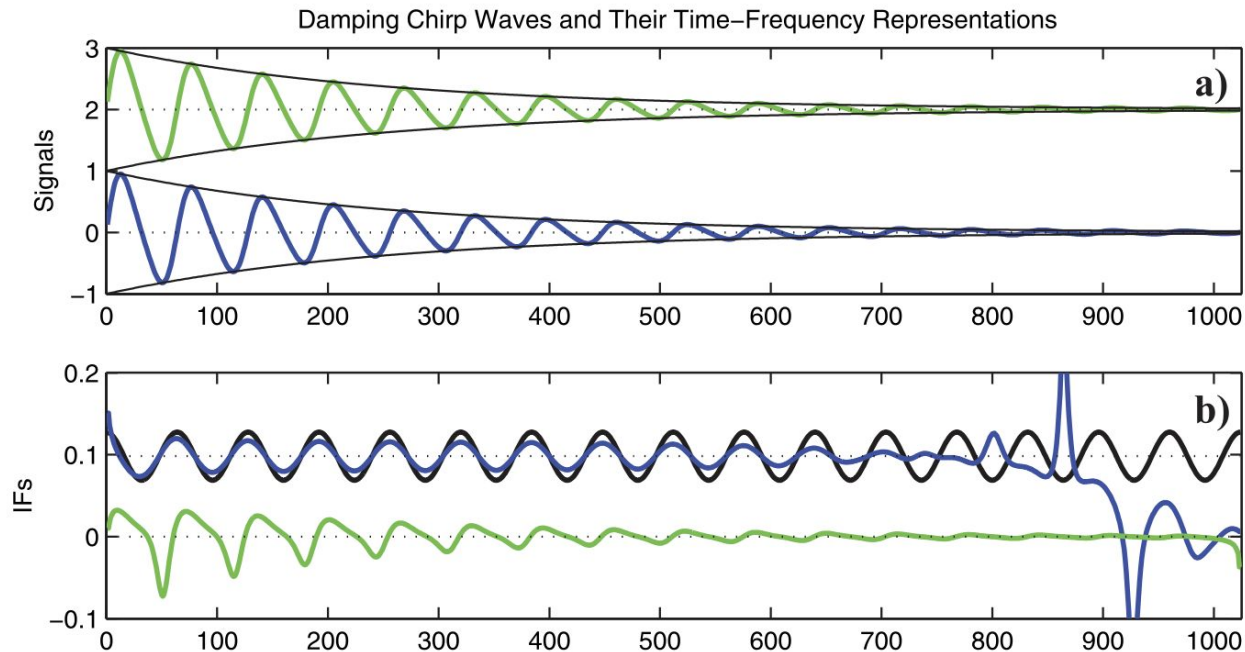
- Instantaneous frequency

$$\omega(t) = \frac{d\theta}{dt}$$

- Energy

$$h(\omega) = \int_0^T H(\omega, t) dt,$$

Limitations



$$x(t) = e^{-t/256} \sin \left[\frac{\pi t}{32} + 0.3 \sin \left(\frac{\pi t}{32} \right) \right]$$

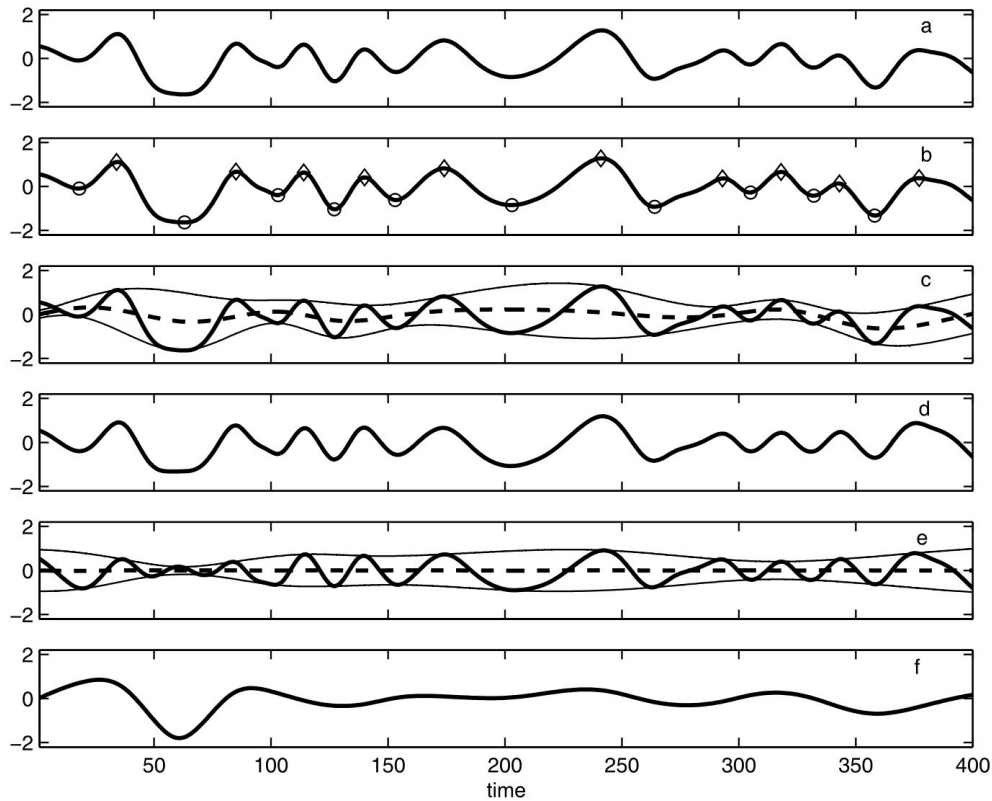
Limitations

- Huang: need a purely oscillatory function with a zero reference level for the Hilbert transform to work
- How to decompose an arbitrary function $x(t)$ in terms of functions with meaningful Hilbert transform?
- Development of the empirical mode decomposition (EMD)

Empirical Mode Decomposition

- Assumes that the data is a superposition of oscillatory modes
- Intrinsic mode function (IMF)
 - Number of extrema and zero crossings must either be equal or differ by one
 - Mean value of the envelopes defined using the local extrema is zero
- Decompose a function through a sifting process

Sifting Process



First protomode

$$h_1 = x(t) - m_1.$$

Sifting Process

- Iterate until protomode satisfies IMF definition

$$h_{1(k-1)} - m_{1k} = h_{1k}$$

$$c_1 = h_{1k}$$

- Purpose
 - Eliminate background waves
 - Make wave profiles more symmetric

Decomposition into IMFs

$$x(t) - c_1 = r_1$$

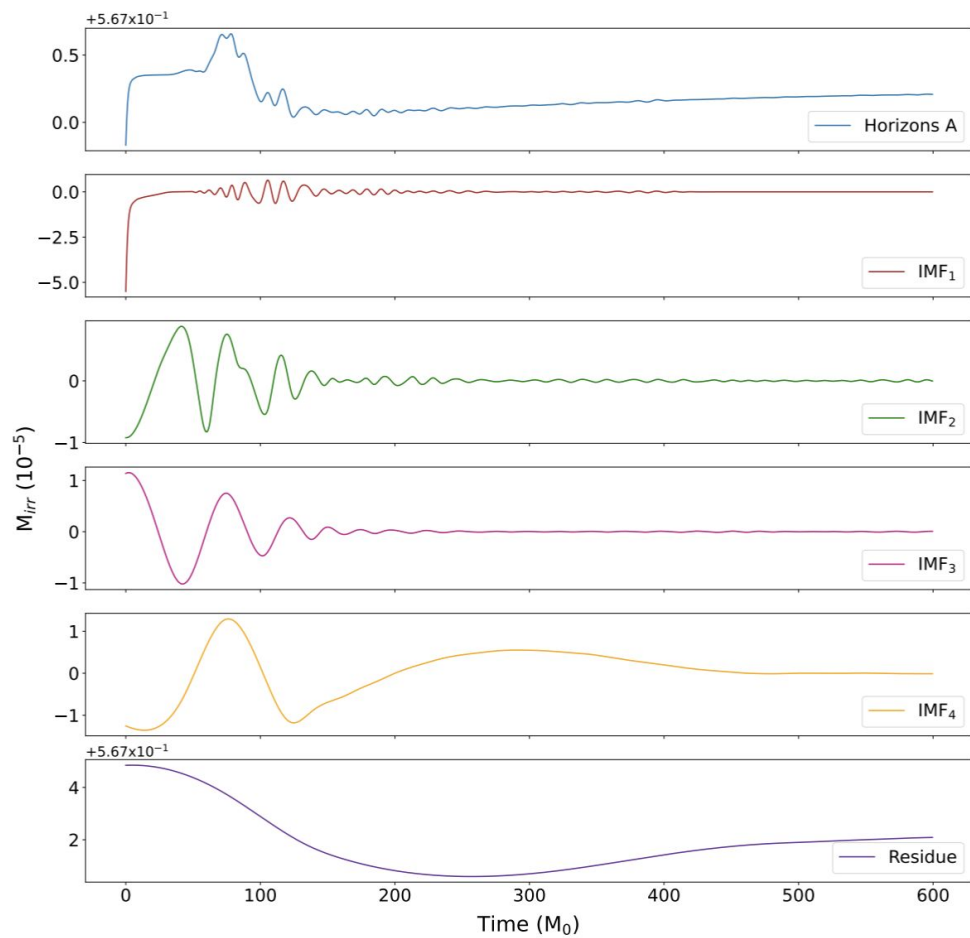
$$r_1 - c_2 = r_2$$

...

$$r_{n-1} - c_n = r_n \longrightarrow$$

Stop when the residue becomes a function that is either monotonic or has only one extremum

$$x(t) = \sum_{j=1}^n c_j + r_n.$$



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Stopping criterion

- When to stop sifting?
- Cauchy type of convergence test

$$\text{SD}_k = \frac{\sum_{t=0}^T |h_{k-1}(t) - h_k(t)|^2}{\sum_{t=0}^T h_{k-1}^2(t)}$$

$$\text{SD}_k = \frac{\sum_{t=0}^T |m_{1k}(t)|^2}{\sum_{t=0}^T |h_{1k}(t)|^2} ;$$

Stopping criterion

- S stoppage: stop sifting when the number of zero crossings and extrema
 - (1) are equal or differ by at most 1
 - (2) stay the same for S consecutive times
- Empirically determined: $3 < S < 8$

Properties of the EMD

- IMFs usually satisfy, empirically, requirements of convergence, completeness, orthogonality and uniqueness
- Express the data as

$$x(t) = \text{Re} \left[\sum_{j=1}^n a_j(t) e^{i\omega_j(t)t} \right]$$

- Fourier representation

$$x(t) = \text{Re} \sum_{j=1}^{\infty} a_j e^{i\omega_j t}$$

Properties of the EMD

- A 'generalized' Fourier transform
- Time-dependent frequency and amplitude
 - Accommodates nonlinear and nonstationary behavior
- Adaptive basis
 - Not subject to any limitations on time/frequency resolutions

Normalized Hilbert Transform

- Variations in the phase function \gg variations in the amplitude

$$x(t) = a(t)\cos\theta(t)$$

- Physically meaningful instantaneous frequency should come only from the phase function

$$H[a(t) \cos \theta(t)] = a(t)H[\cos \theta(t)]$$

Normalized Hilbert Transform

- Bedrosian Theorem

$$H[f(t)h(t)] = f(t)H[h(t)]$$

True, only if

- (1) Fourier spectra of $f(t)$ and $h(t)$ do not overlap, and
- (2) Frequency range of the spectrum of $h(t) \gg$ frequency range of the spectrum of $f(t)$

Normalized Hilbert Transform

- Separate IMF into amplitude (AM) and frequency (FM) modulation parts
- Apply the Hilbert transform to the FM part only
- Algorithm

- (1) Find the absolute value of the IMF
- (2) Identify the maxima
- (3) Define an envelope through the maxima

(4) Normalize:
$$f_1(t) = \frac{x(t)}{e_1(t)}$$

Normalized Hilbert Transform

- Iterate

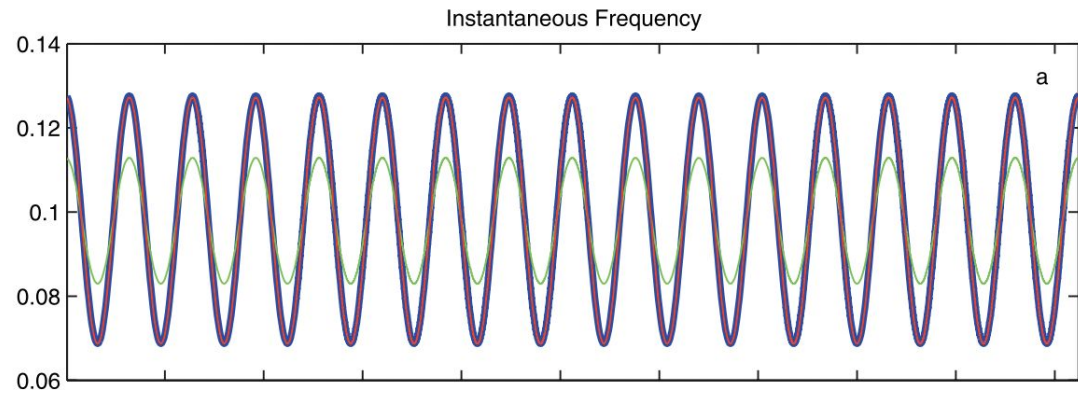
$$f_2(t) = \frac{f_1(t)}{e_2(t)}; \dots f_n(t) = \frac{f_{n-1}(t)}{e_n(t)}$$

- Define the FM and AM components as

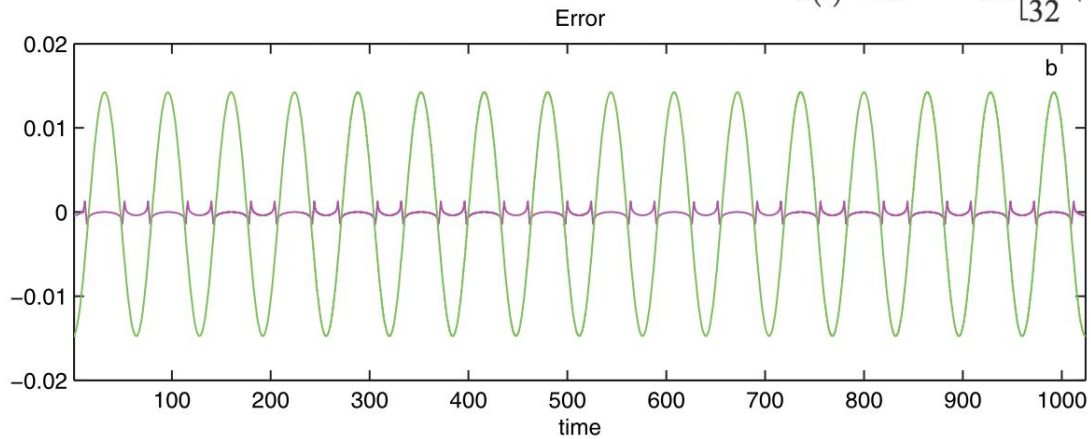
$$F(t) = f_n(t)$$

$$A(t) = \frac{x(t)}{F(t)}$$

- Normalized Hilbert transform = normalization + Hilbert transform applied to the FM part

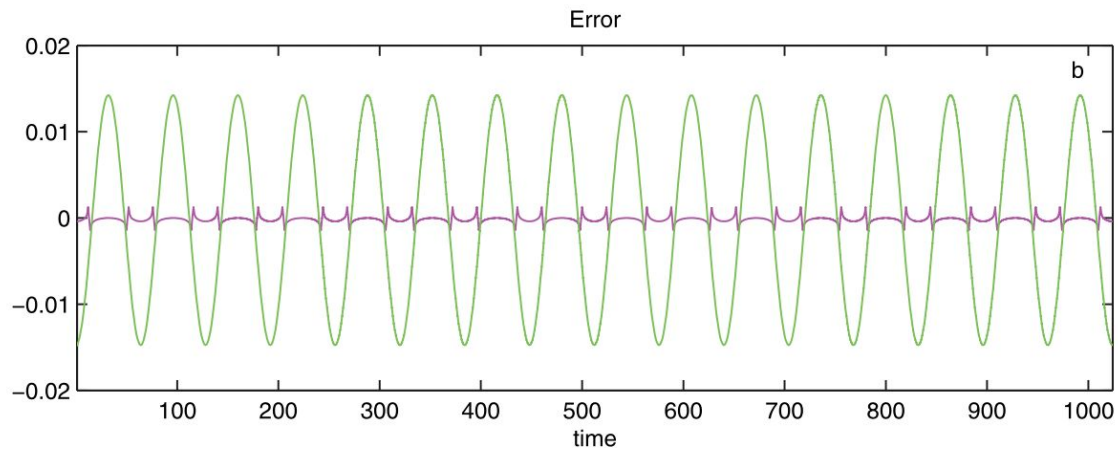
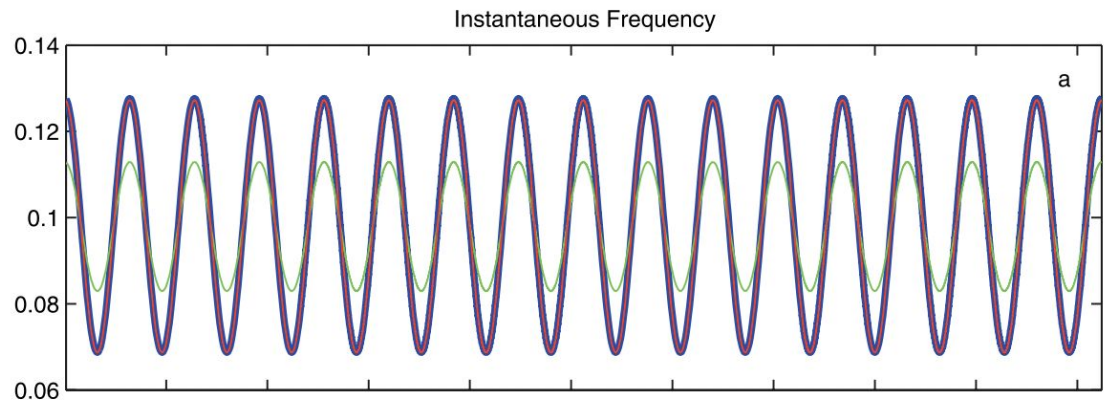


$$x(t) = e^{-t/256} \sin\left[\frac{\pi t}{32} + 0.3 \sin\left(\frac{\pi t}{32}\right)\right]$$



Direct Quadrature Method

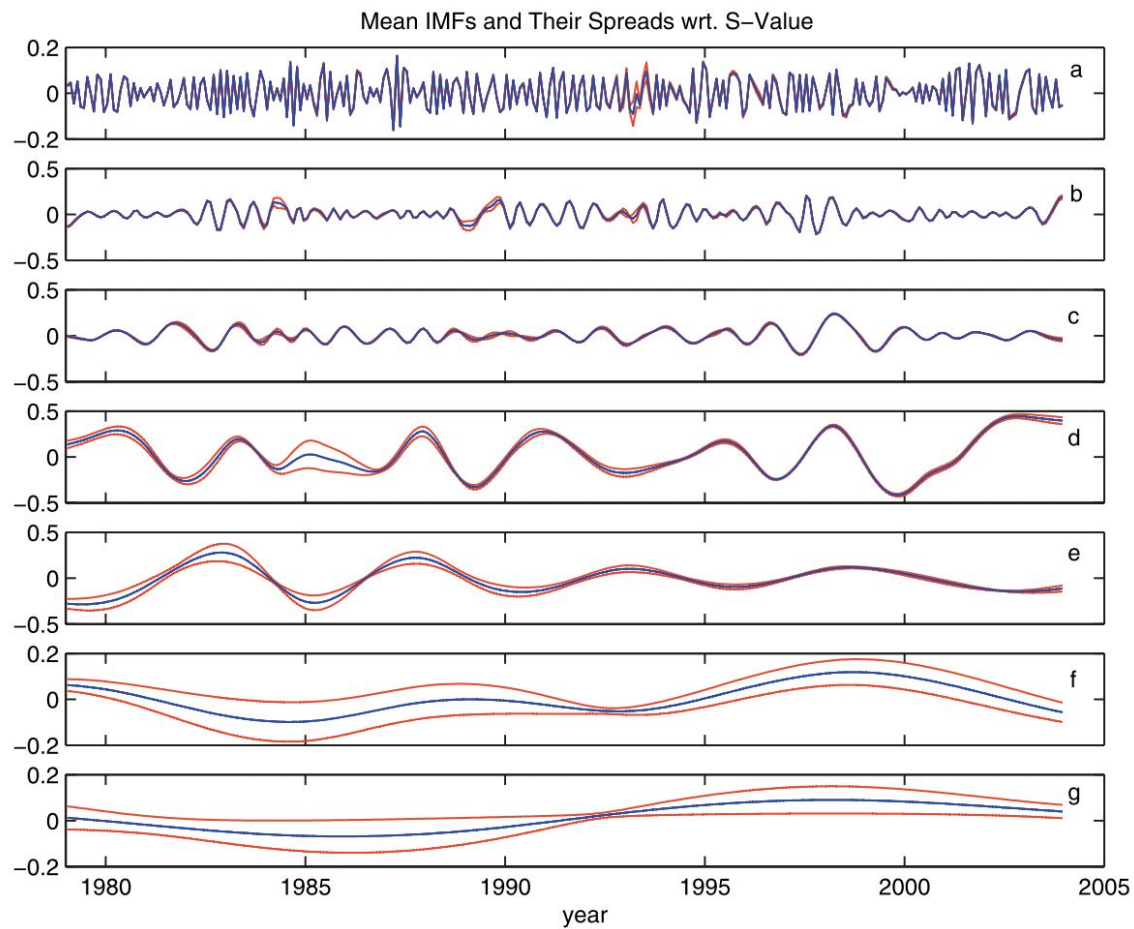
- Hilbert transform underestimates the true frequency
- Direct Quadrature Method
 - What if we just take advantage of the good properties of the IMF?
 - Data \rightarrow IMFs \rightarrow AM + FM \rightarrow arccos of phase function



Confidence Limit

- Need a criterion to measure the reliability of the decomposition
- How sensitive are the results to the stopping criterion?
- Check for 'convergence' of IMFs by using different values of stopping criterion
- Calculate the mean and the spread for different sets of n IMFs

$$4 < S < 13$$



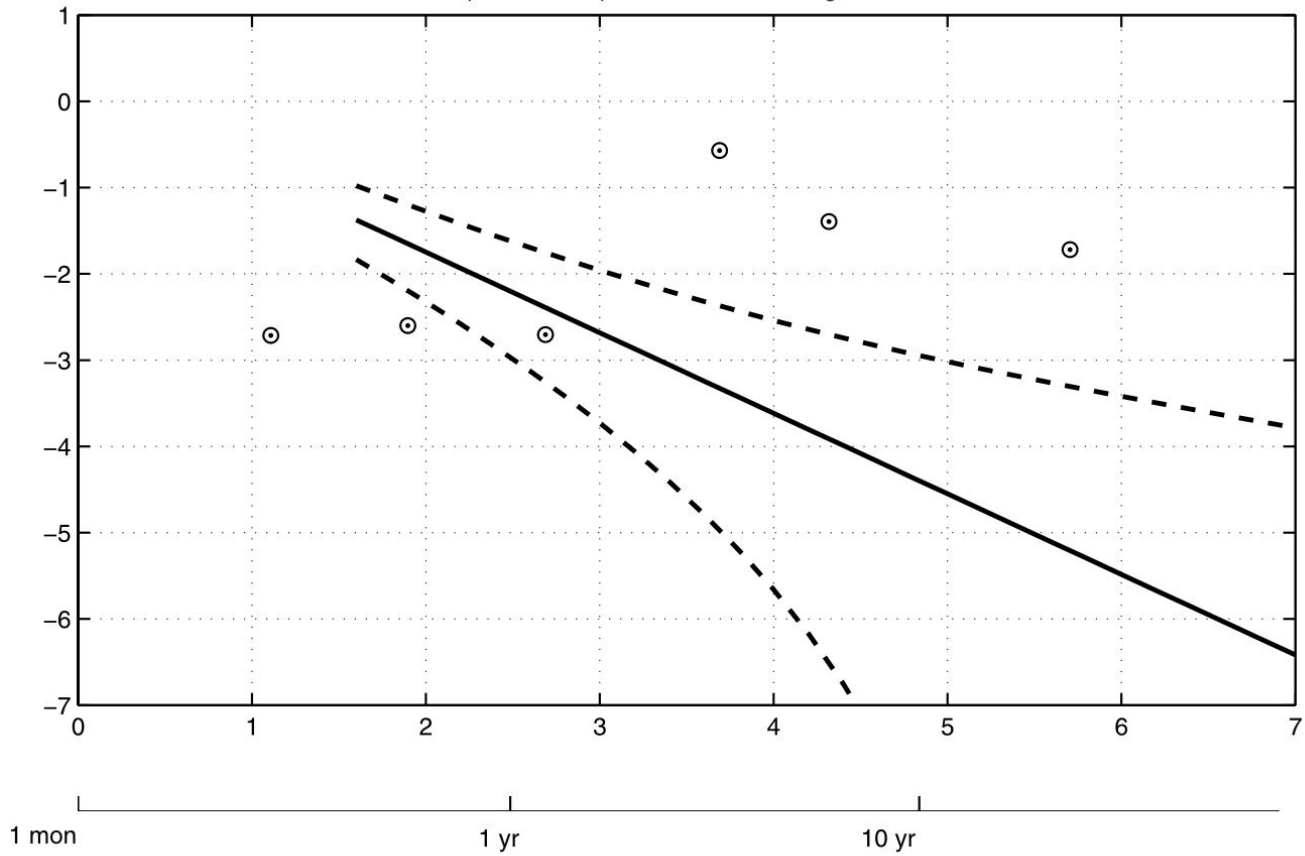
Statistical Significance

- Data is usually noisy
- How to know whether an IMF is a component of noise?
- Spectral properties of noise in the EMD
 - *Flandrin et al., Flandrin and Golcalves*: Gaussian noise
 - *Wu and Huang*: white noise

Statistical Significance

- Common properties
 - Spectra of all IMFs, except the first one, collapse to a single shape, with the appropriate amplitude scaling
 - Center frequencies of neighboring IMFs are halved
- Derive the expected energy distribution of IMFs of a noise series
- Central Limit Theorem: E follows a χ^2 distribution \rightarrow analytic form for the spread S
- Expected energy distribution + spread \rightarrow statistical significance test

A priori and A posteriori Tests of Significance



Statistical Significance

- Monte Carlo test
 - (1) Generate a large sample of the noise series
 - (2) Decompose into IMFs
 - (3) Find the statistical distribution of the metric of interest
 - (4) Compare the location of the same metric evaluated on the data with this distribution

