

Hilbert-Huang Transform to Estimate Turbulent Diffusion Coefficient from **a** **Single** Lagrangian Drifter Trajectory

Peter C. Chu
Naval Postgraduate School
Monterey, California, USA

Outline

- 1. Introduction
- 2. Hilbert-Huang Transform (HHT)
Empirical Mode Decomposition (EMD)
- 3. Separation of Deterministic and Stochastic Components
- 4. Determination of (K_x, K_y)
- 5. Conclusions

1. Introduction

Eddy Diffusivity

Multiple Lagrangian Drifters

$$[x_n(m), y_n(m)], [u_n(m), v_n(m)]$$
$$n = 1, 2, \dots, N; m = 1, 2, \dots, M$$

$N \rightarrow$ Number of drifters

$M \rightarrow$ Number of time instances

$$K_x(m) = c \hat{\sigma}_u(m) \hat{\sigma}_x(m)$$

$$K_y(m) = c \hat{\sigma}_v(m) \hat{\sigma}_y(m)$$

Okubo and Ebbsmeyer
(1976 DSR)



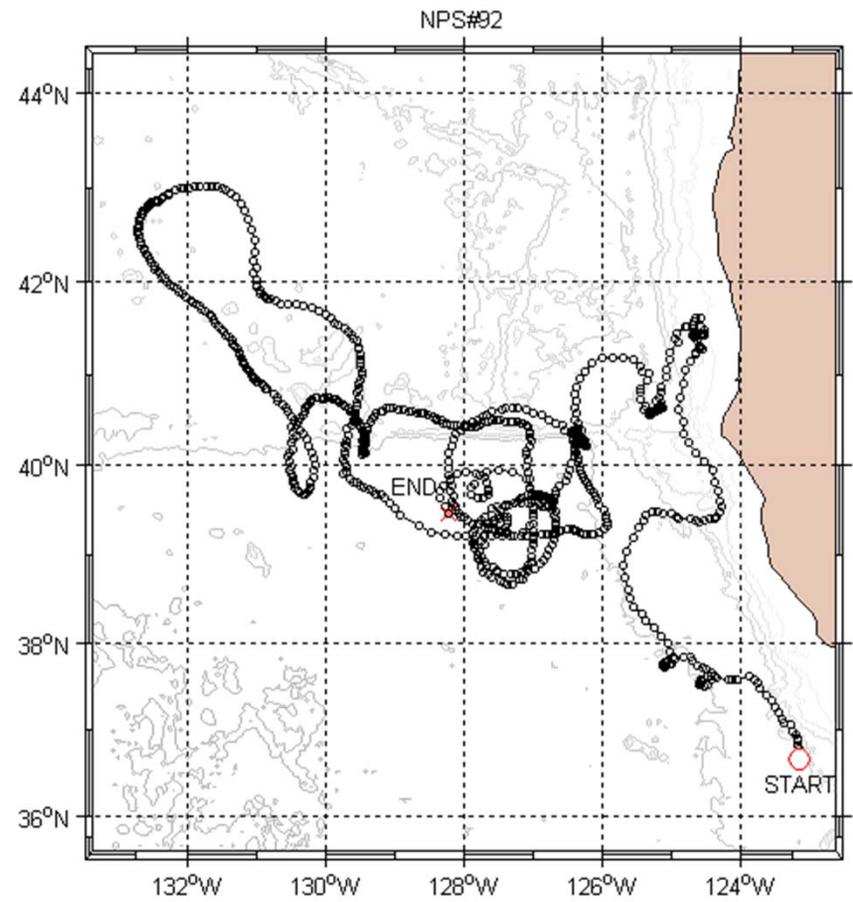
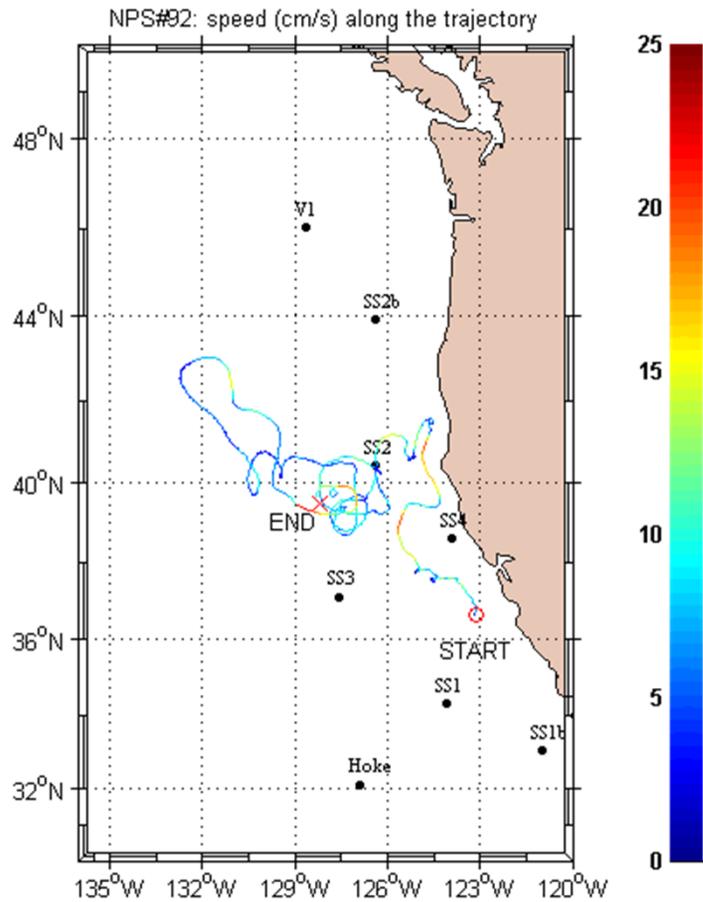
Minimum Number of Drifters

$$\hat{\sigma}_x(m) = \sqrt{\frac{1}{(N-1)} \sum_{n=1}^N [x_n(m) - \bar{x}(m)]^2}$$
$$\hat{\sigma}_y(m) = \sqrt{\frac{1}{(N-1)} \sum_{n=1}^N [y_n(m) - \bar{y}(m)]^2}$$
$$\bar{x}(m) = \frac{1}{N} \sum_{n=1}^N x_n(m), \quad \bar{y}(m) = \frac{1}{N} \sum_{n=1}^N y_n(m)$$

N > 6 (Okubo and Ebbesmeyer, 1976) → Statistical meaningful

$$(\hat{\sigma}_x, \hat{\sigma}_x, \hat{\sigma}_u, \hat{\sigma}_v)$$

What Happen if N is much smaller than 6?



NPS RAFOS Subsurface Data: <http://www.oc.nps.edu/npsRAFOS/>

Can the turbulent eddy diffusivity
be determined from a **single**
Lagrangian drifter?

2. Hilbert-Huang Transform (HHT)

FFT →

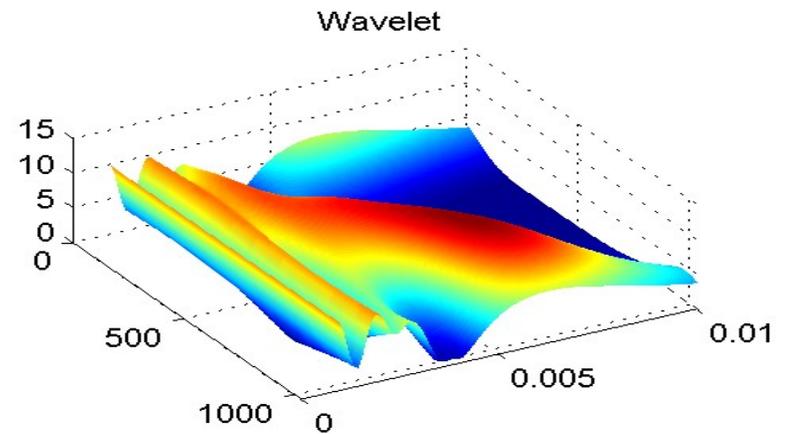
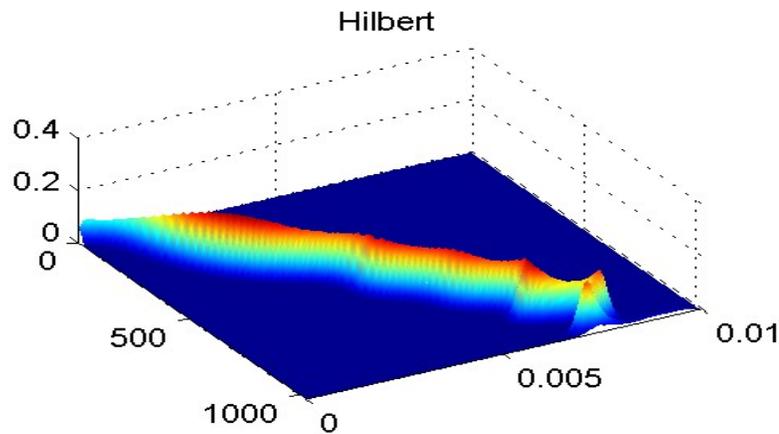
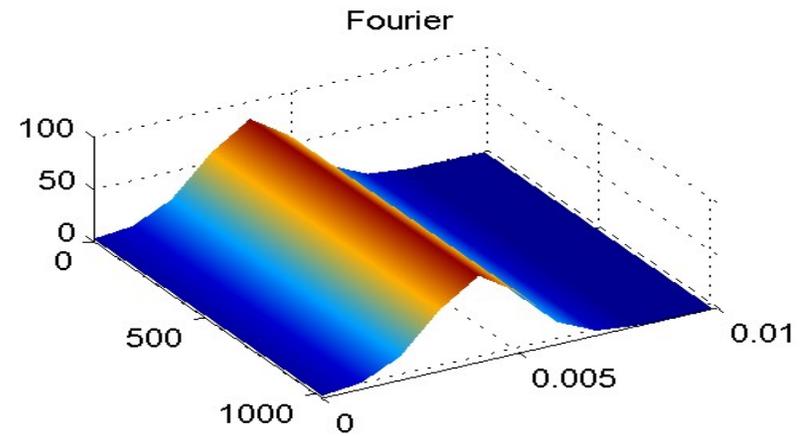
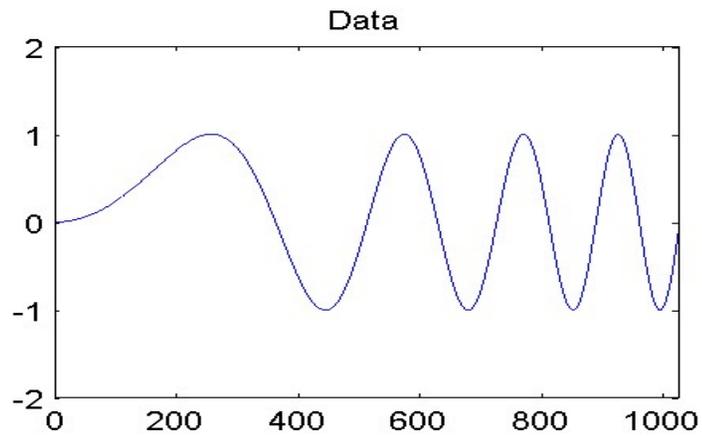
$$x(t) = \Re \sum_j a_j e^{i\omega_j t}$$

HHT →

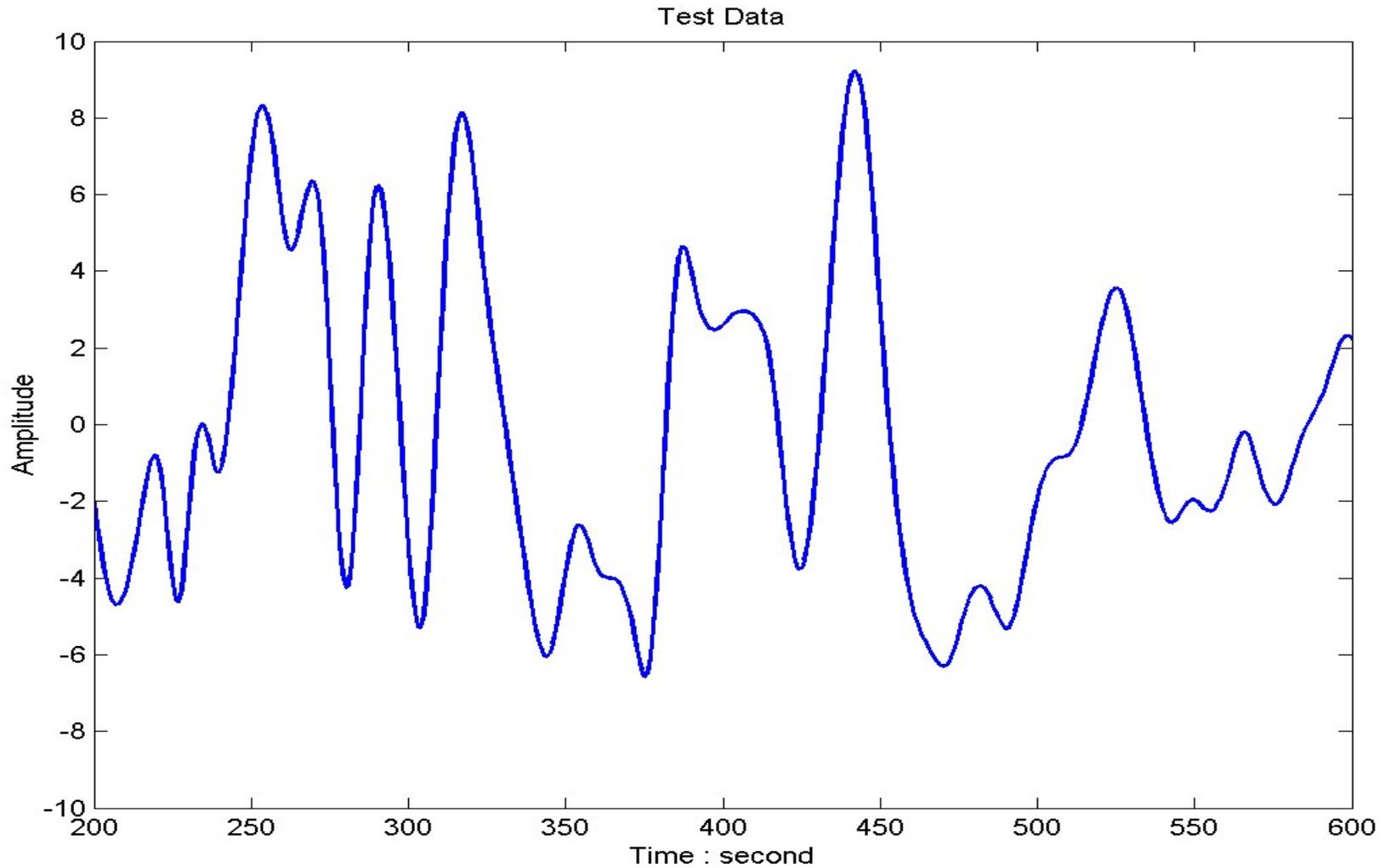
$$x(t) = \Re \sum_j a_j(t) e^{i \int_t \omega_j(\tau) d\tau}$$

Comparisons: Fourier, Hilbert & Wavelet

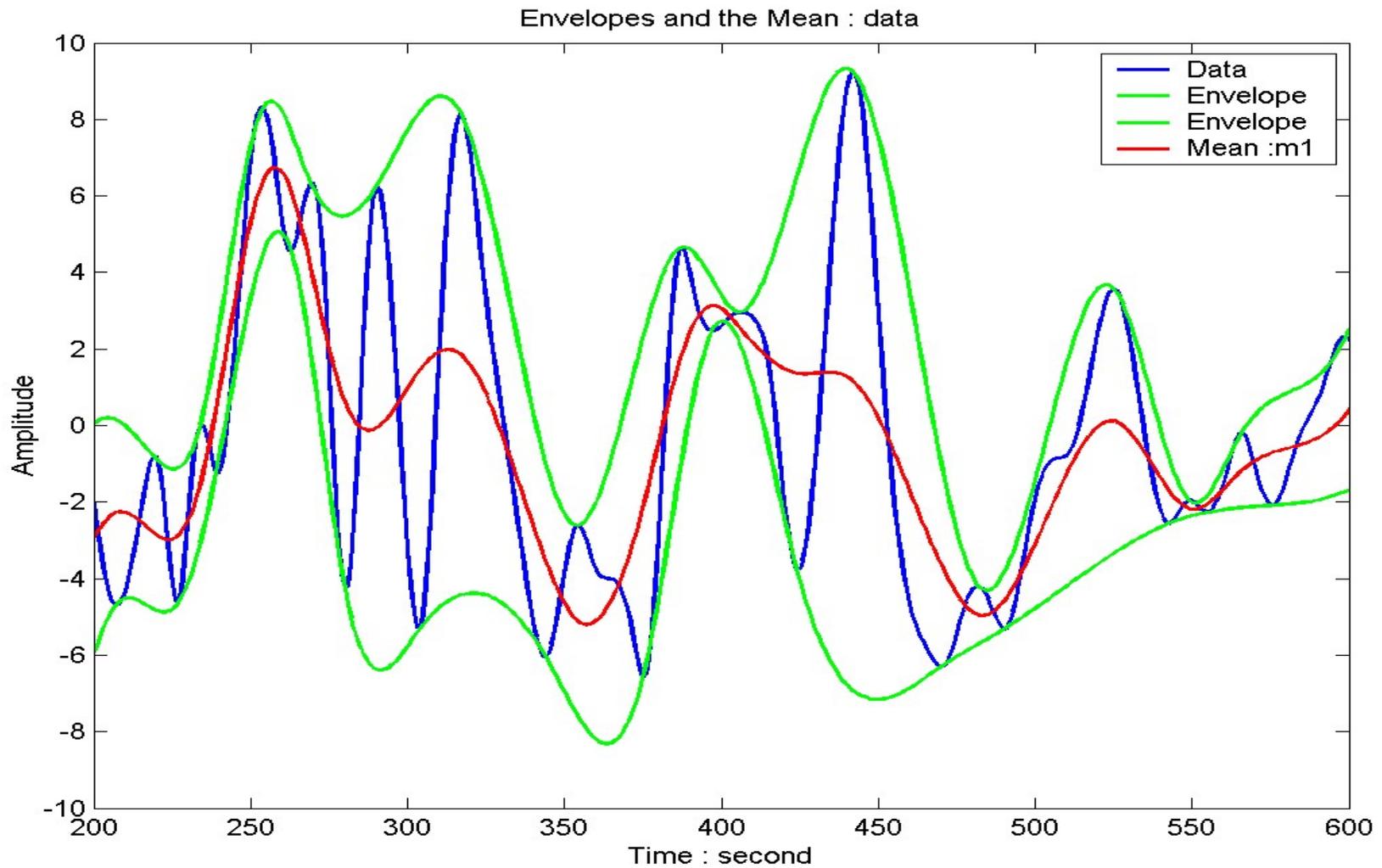
Comparison among Fourier, Hilbert, and Morlet Wavelet Spectra



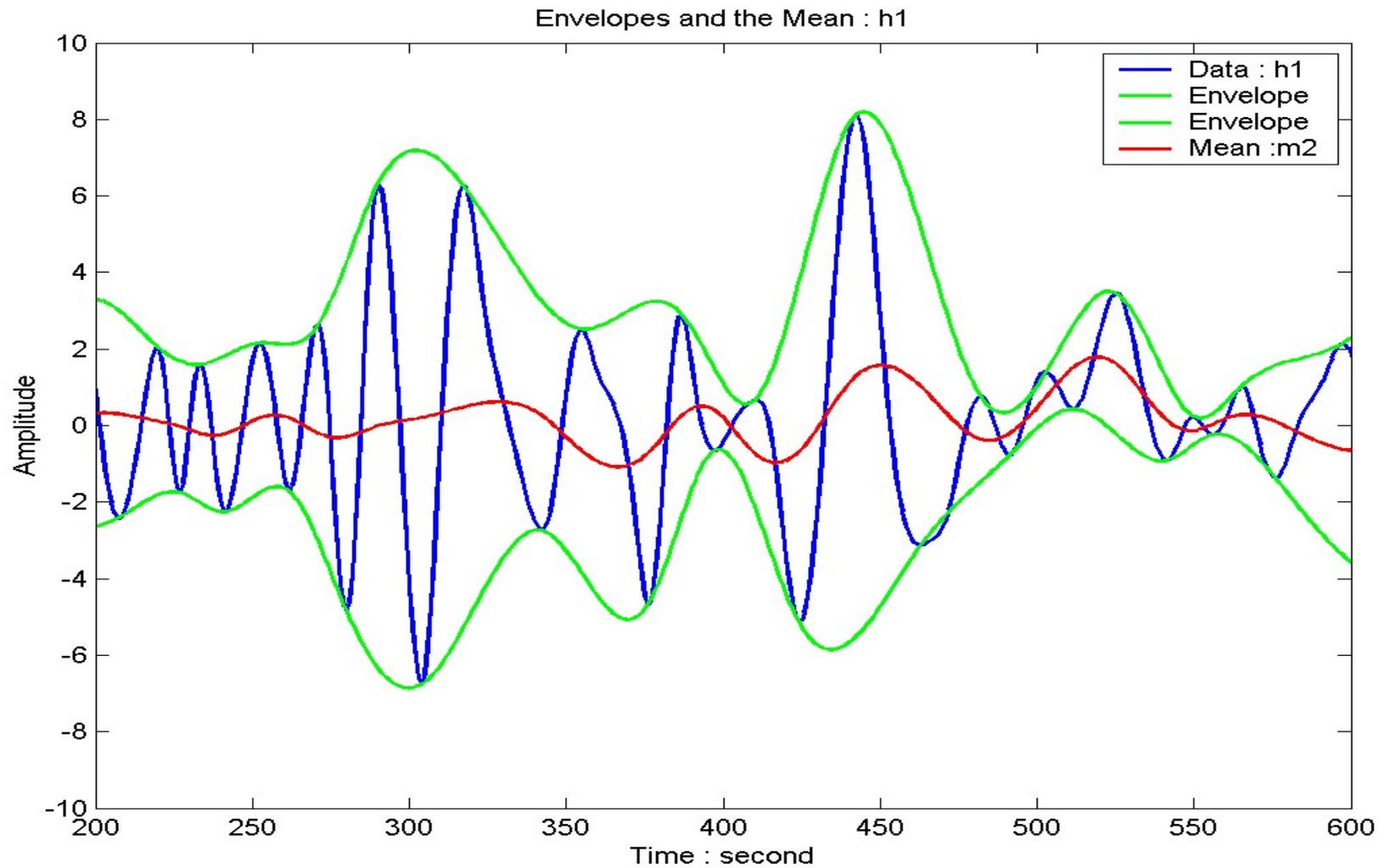
Empirical Mode Decomposition: Methodology : Test Data



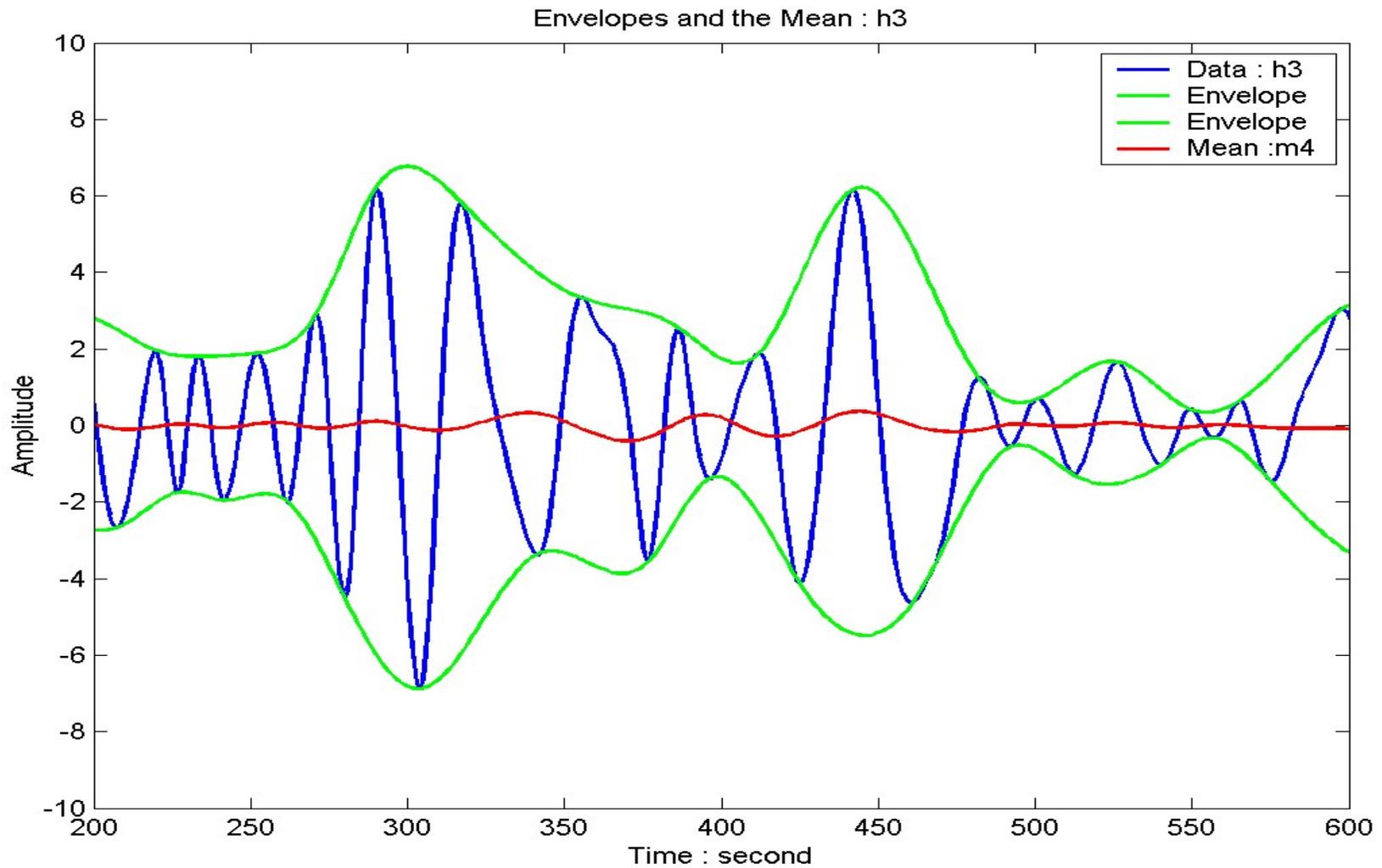
Empirical Mode Decomposition: Methodology : data and m1



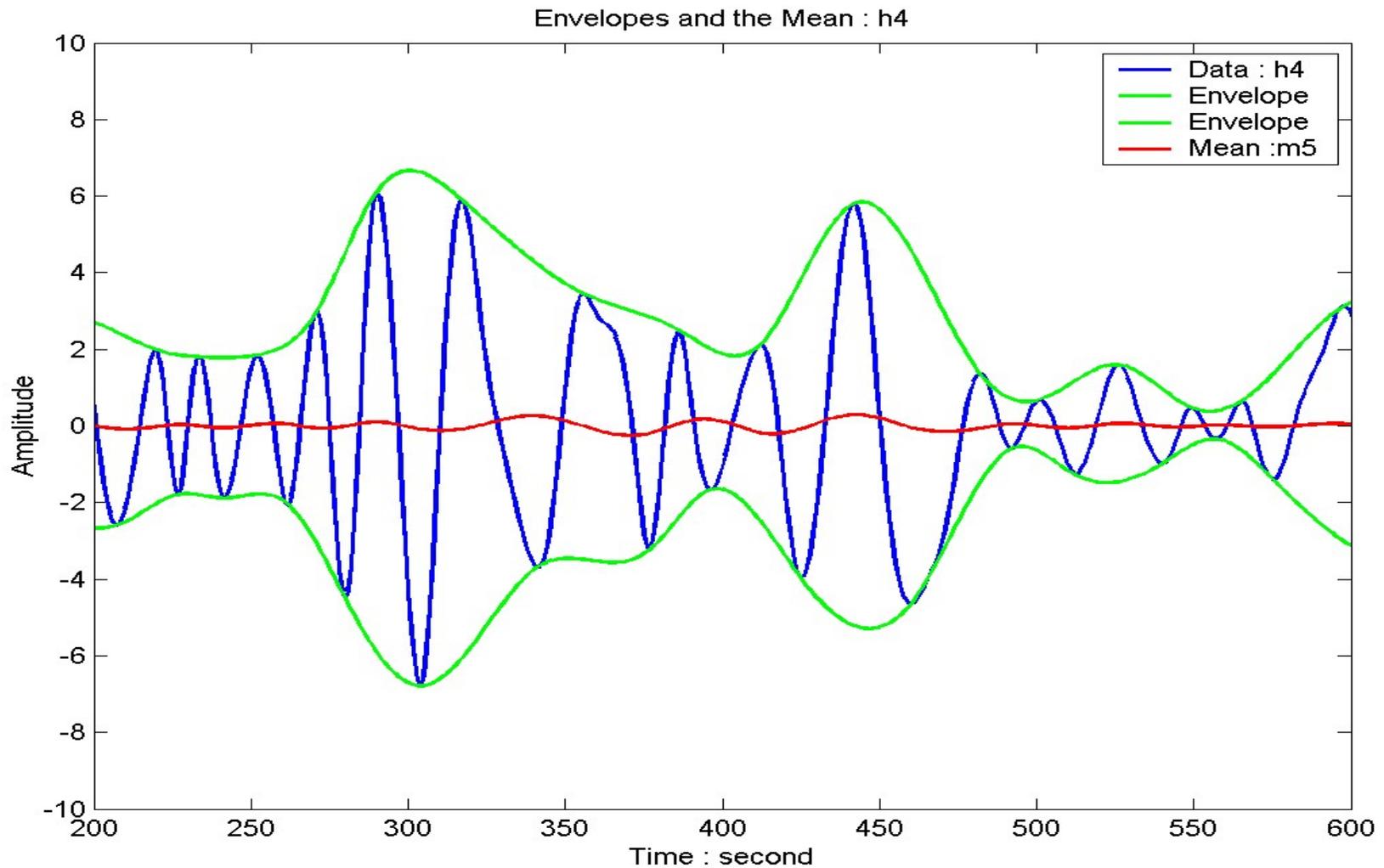
Empirical Mode Decomposition: Methodology : h1 & m2



Empirical Mode Decomposition: Methodology : h3 & m4



Empirical Mode Decomposition: Methodology : h4 & m5



Empirical Mode Decomposition

Sifting : to get one IMF component

$$x(t) - m_1(t) = x_1(t),$$

$$m_1(t) - m_2(t) = x_2(t),$$

.....

$$m_{k-1}(t) - m_k(t) = x_k(t).$$

$$\Rightarrow x(t) = m_K(t) + \sum_{k=1}^K x_k(t).$$

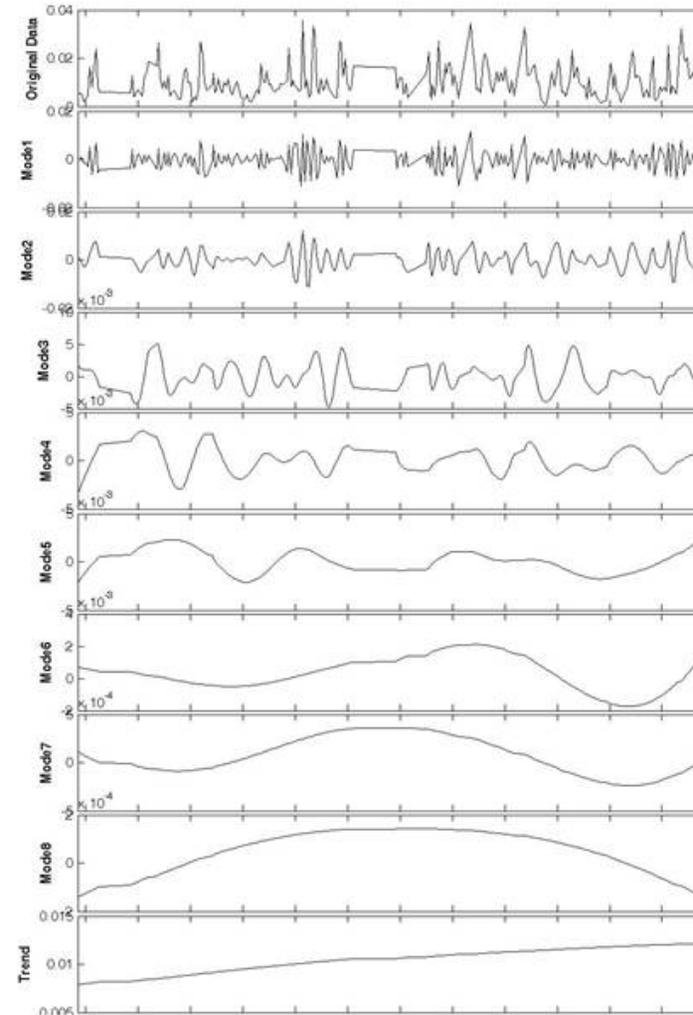
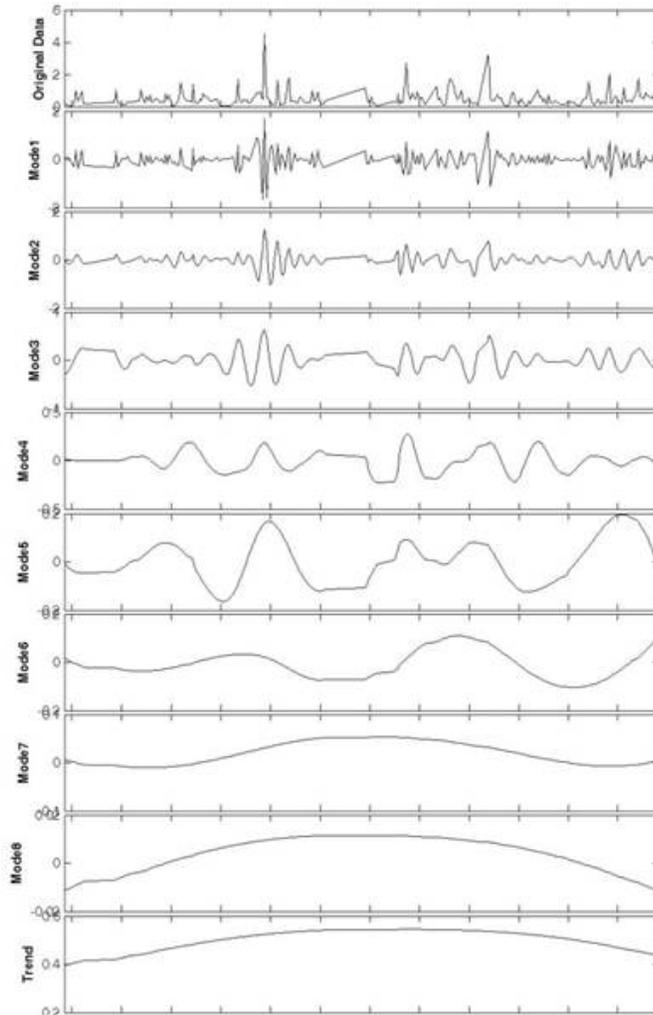
$x_k(t)$ → Intrinsic Mode Function (IMF)

$m_K(t)$ → Trend

3. Separation of Deterministic and Stochastic Components

EMD of a Single Drifter Trajectory $[x(t), y(t)]$

→ Multi-scales



Hilbert Transform on Each IMF → Hilbert-Huang Transform

$$z_k(t) = c_k(t) + i\hat{c}_k(t), \quad i \equiv \sqrt{-1}$$

$$\hat{c}_k(t) = \frac{1}{\pi} CP \int_{-\infty}^{+\infty} \frac{c_k(s)}{t-s} ds,$$

CP is the Cauchy principal value

Instantaneous Amplitude and Frequency

$$z_k(t) = c_k(t) + i\hat{c}_k(t) = a_k(t) \exp[i\theta_k(t)],$$

$$\omega_k(t) = d\theta_k(t) / dt \quad \rightarrow \text{Instantaneous Frequency}$$

$$a_k(t) \quad \rightarrow \text{Instantaneous Amplitude}$$

Separation of Deterministic and Stochastic IMFs

- Rios & de Mello' Method (2016, Signal Processing, 118, 159-176)
- Phase Spectra

$$\theta_k(t) \rightarrow \begin{cases} \text{low frequency} \rightarrow \text{Deterministic} \\ \text{high frequency} \rightarrow \text{Stochastic} \end{cases}$$

4. Determination of (K_x , K_y)

The first 7 IMFs → high frequency

→ Stochastic

The last three IMFs → low frequency

→ Deterministic

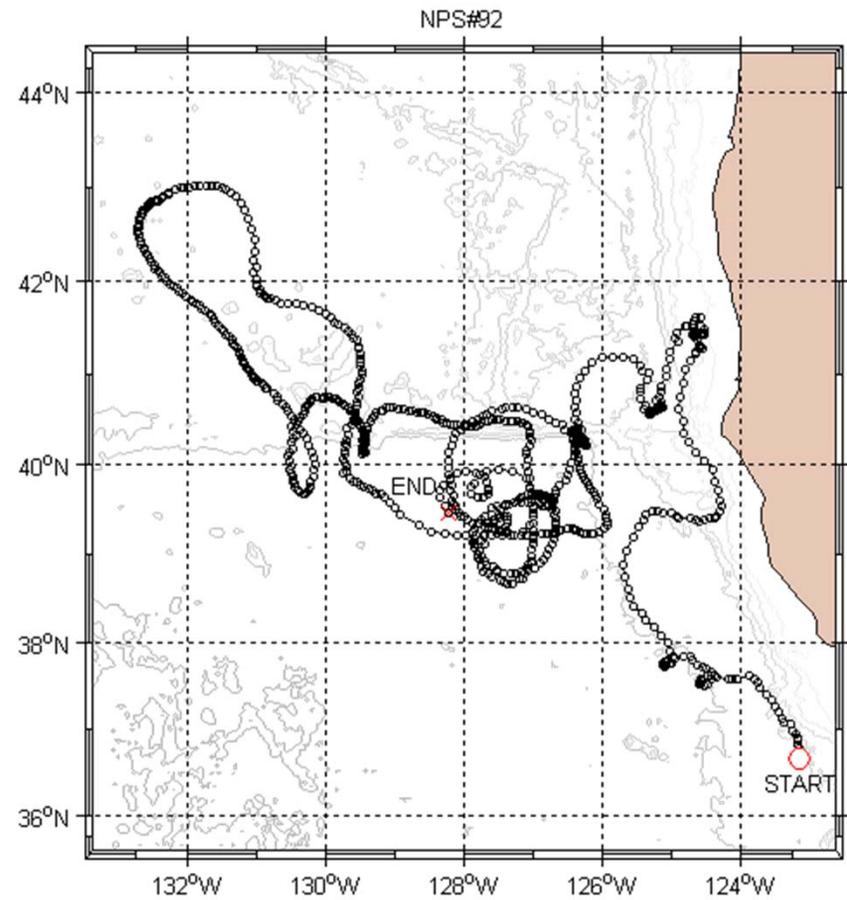
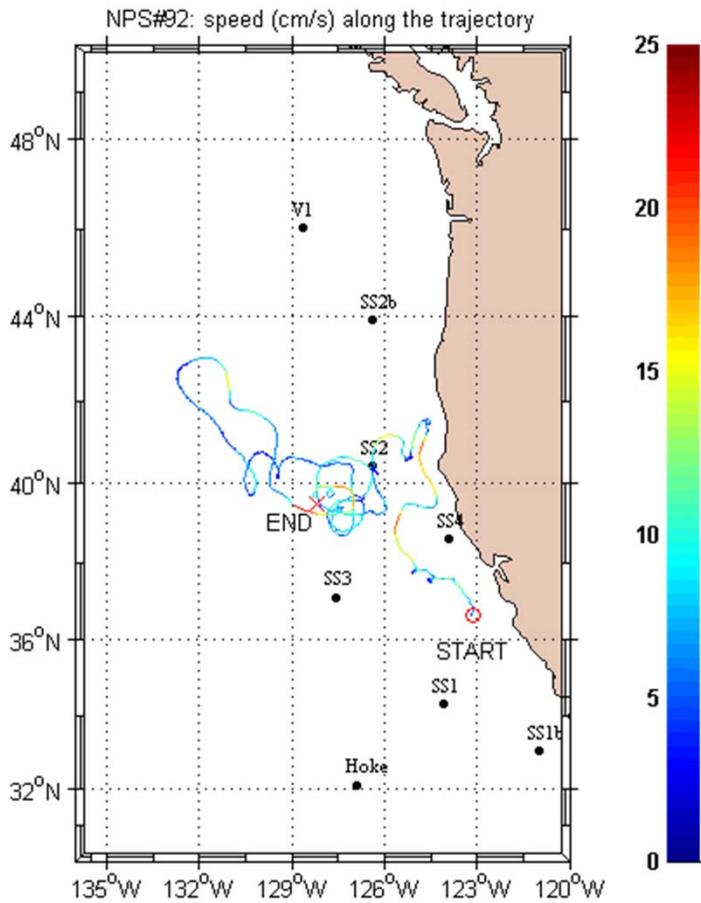
High-Frequency IMFs → Set of “Trajectories”

$$[x_n(m), y_n(m)], [u_n(m), v_n(m)]$$
$$n = 1, 2, \dots, 7; m = 1, 2, \dots, M$$

$$K_x(m) = c \hat{\sigma}_u(m) \hat{\sigma}_x(m)$$
$$K_y(m) = c \hat{\sigma}_v(m) \hat{\sigma}_y(m)$$

Temporally averaged (K_x, K_y) are the eddy diffusivities of the single Lagrangian drifter

$$K_x \approx 1.27 \times 10^7 \text{ cm}^2 / \text{s}, \quad K_y \approx 0.86 \times 10^7 \text{ cm}^2 / \text{s}$$



NPS RAFOS Subsurface Data: <http://www.oc.nps.edu/npsRAFOS/>

4. Conclusions

- Turbulent eddy diffusivity can be identified from **a single** Lagrangian drifter.
- EMD is a simple and effective method.
- Other methods such as Wavelet, S-transform may also be used.