

# Hilbert-Huang Transform(HHT)

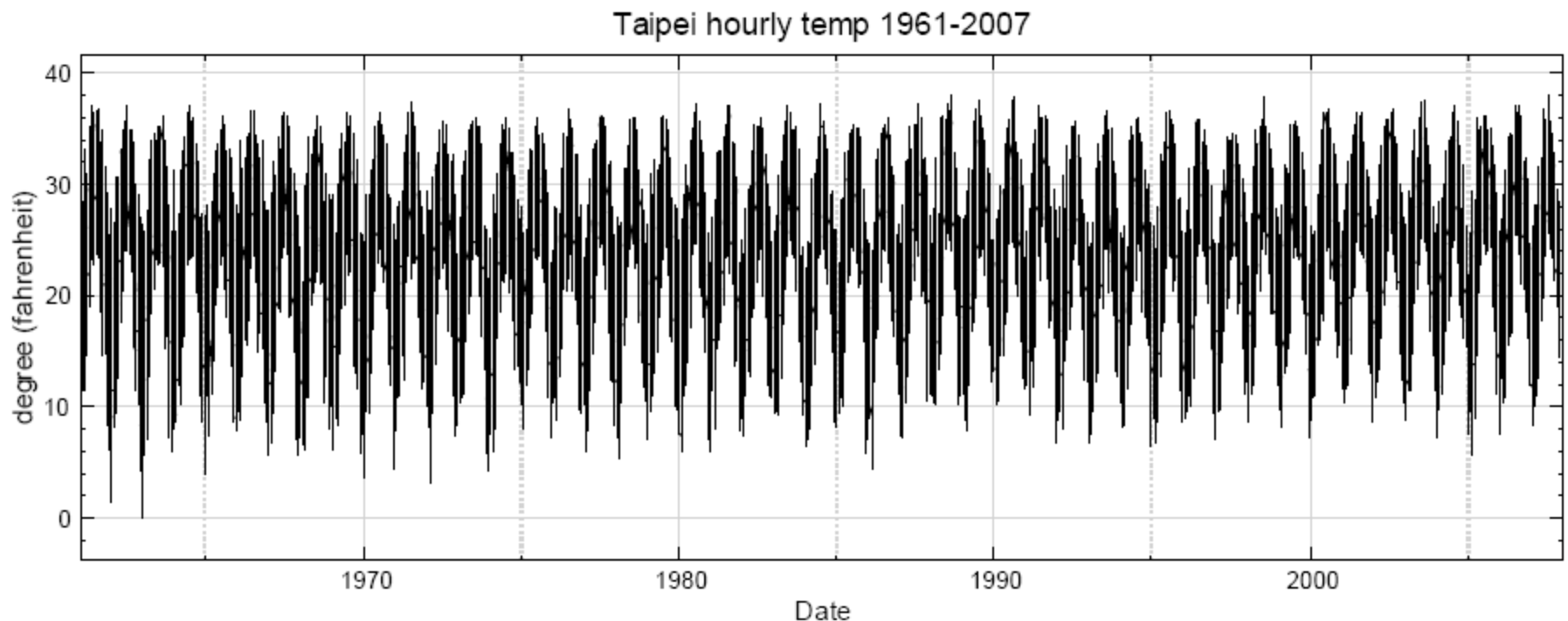
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# Motivation

- ❖ To deal with nonlinear and non-stationary signal
- ❖ To get Instantaneous frequency(IF)



# Hilbert Transform

- ❖ The Hilbert transform can be thought of as the convolution of  $s(t)$  with the function  $h(t) = 1/(\pi t)$

$$\hat{s}(t) = s(t) * \frac{1}{\pi t}$$

- ❖ Derive the analytic representation of a signal

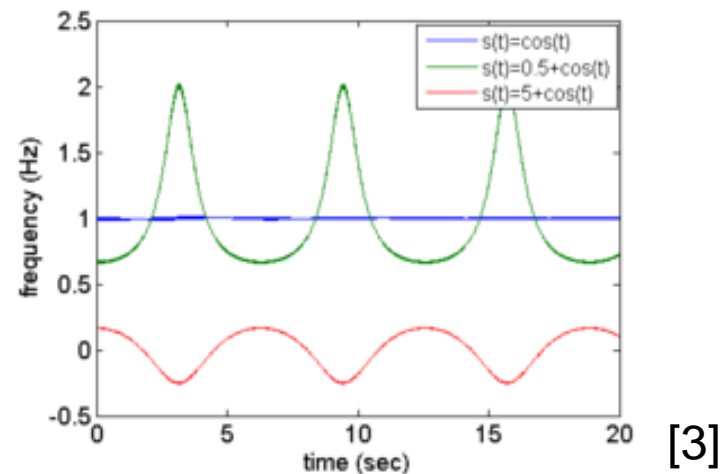
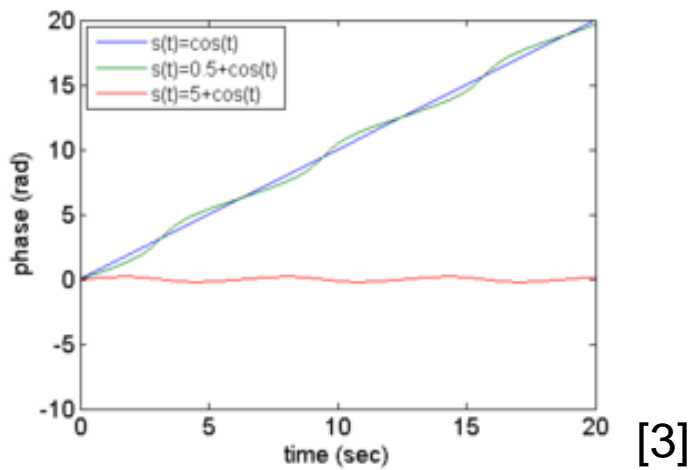
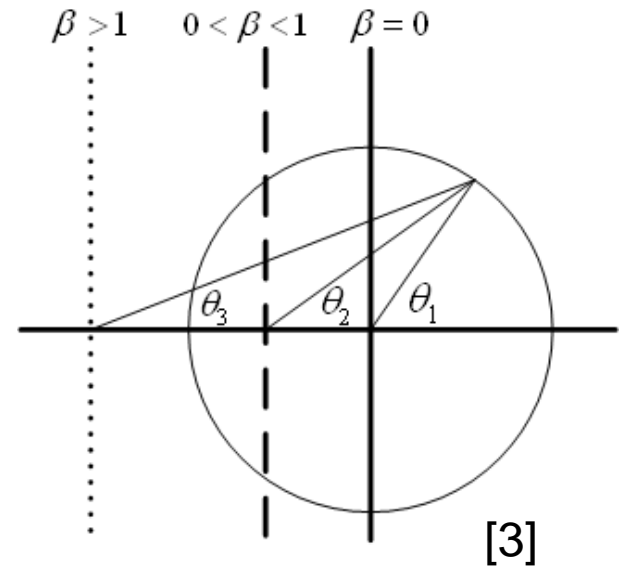
$$z(t) = s(t) + j\hat{s}(t) = m(t) \cdot e^{j\theta(t)}$$

$$\text{Instantaneous Frequency : } f(t) = \frac{d}{dt} \theta(t)$$

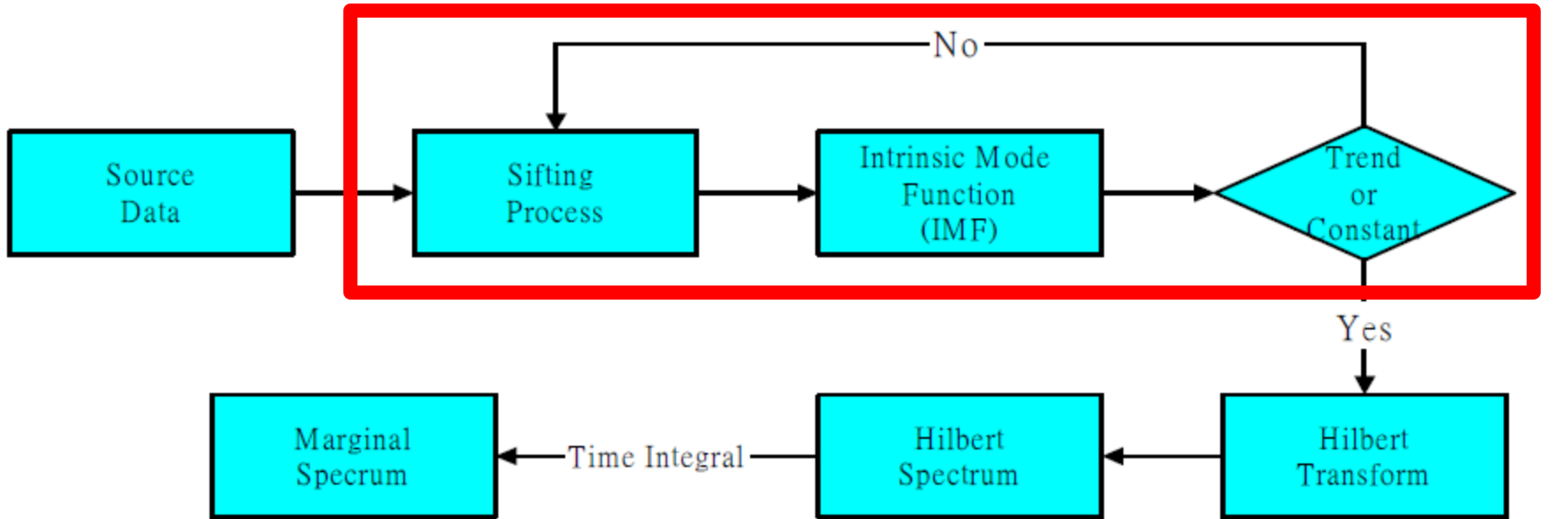
# Instantaneous Frequency(IF)

❖  $s(t) = \beta + \cos(t)$

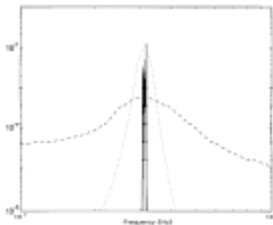
- ❖ (1)  $\beta = 0$ : IF is the constant
- ❖ (2)  $0 < \beta < 1$ : IF has been oscillating
- ❖ (3)  $\beta > 1$ : IF has been negative



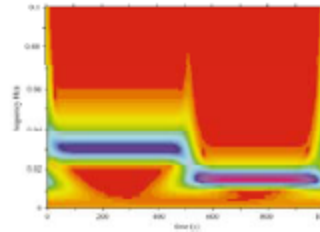
# Flow Chart



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



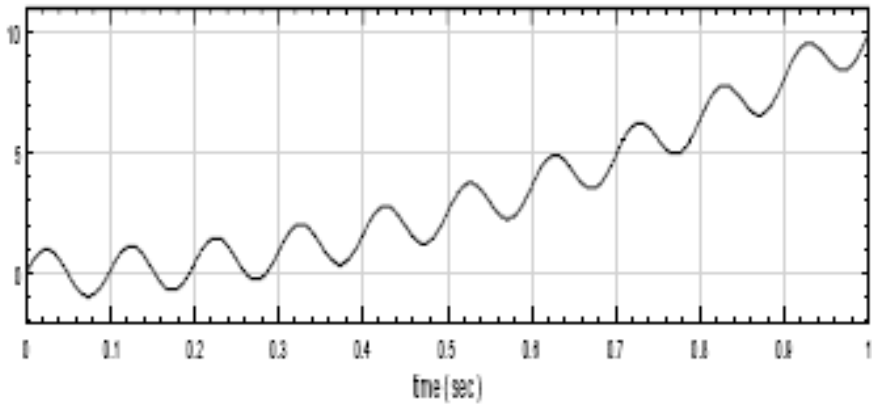
$$X(t) = \sum_{j=1}^n a_j(t) e^{i2\pi \int f_j(t) dt}$$



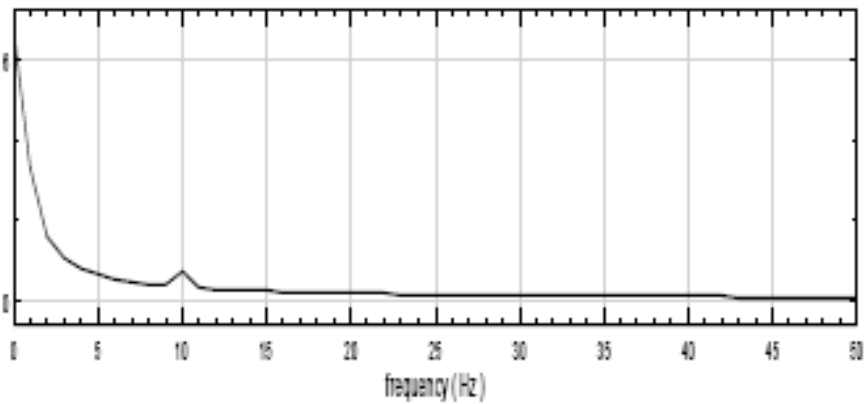
$$Y(t) = \frac{1}{\pi} PV \int_{-\infty}^{\infty} \frac{X(t')}{t-t'} dt'$$

# Example

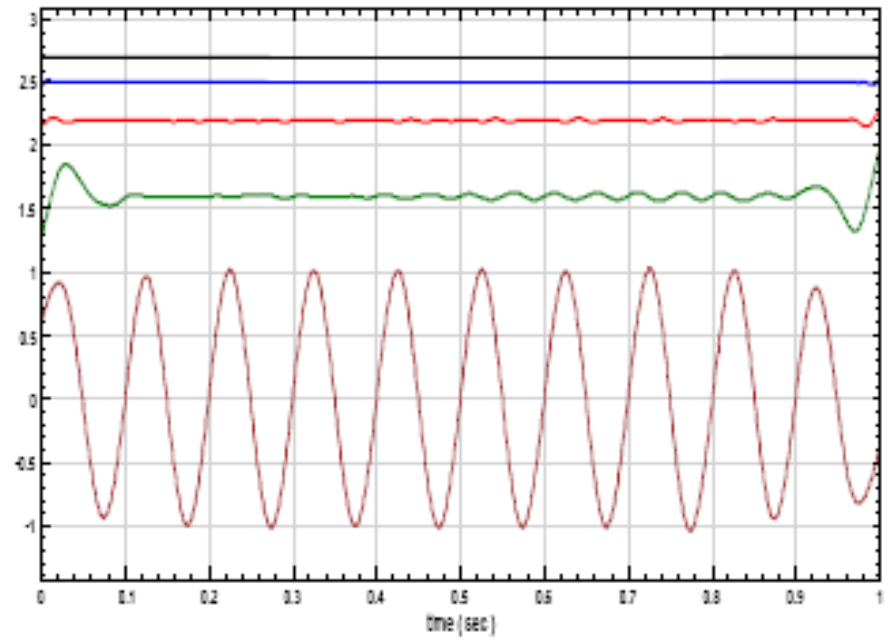
CustomWave



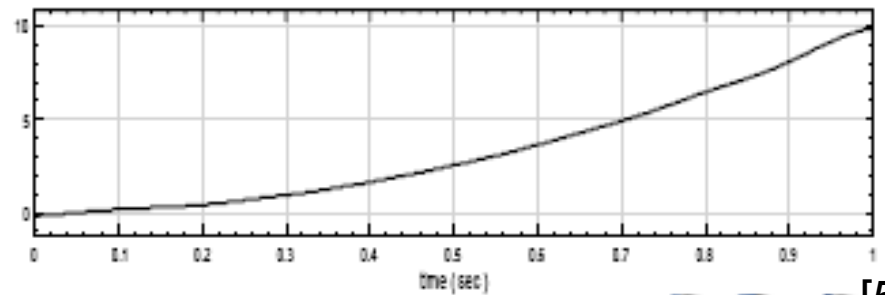
CustomWave-FFT



View IMF

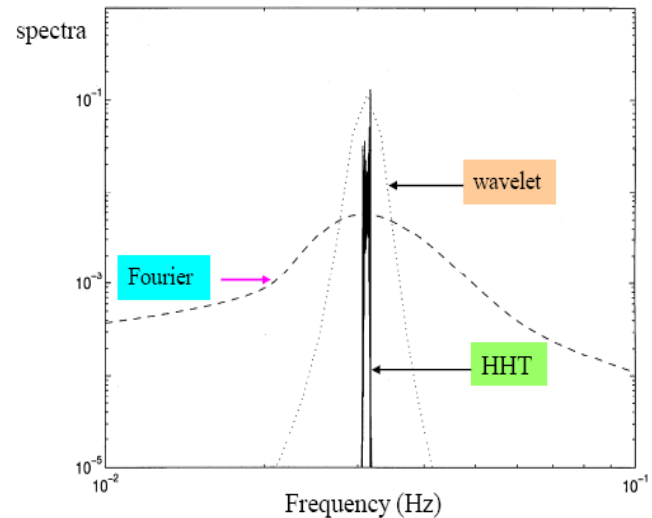











View Residual



# Time–Frequency Analysis

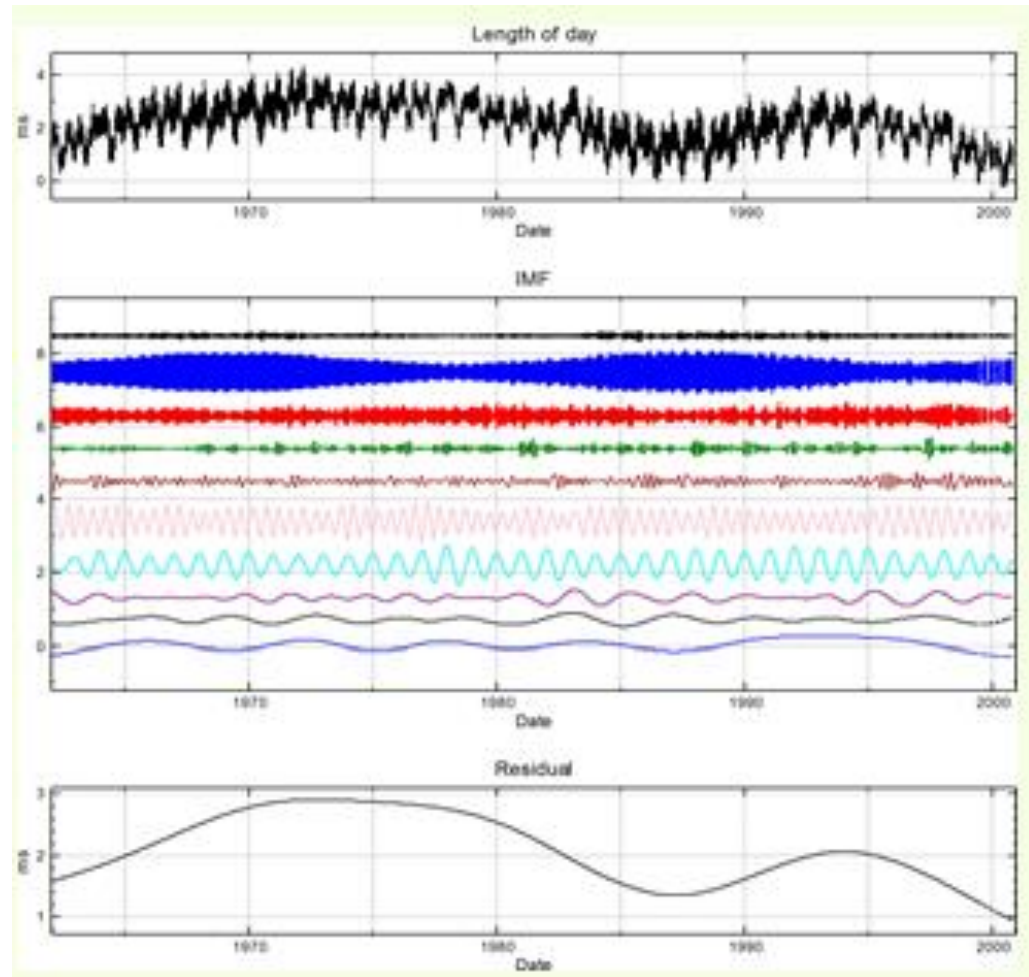
- ❖ Fast Fourier Transform (FFT)
- ❖ Wavelet Transform
- ❖ Hilbert-Huang Transform (HHT)



	FFT	Wavelet	HHT
Basis	<i>a priori</i>	<i>a priori</i>	Adaptive
Nonlinear			
Non-stationary			
Feature Extraction			

# Geoscience

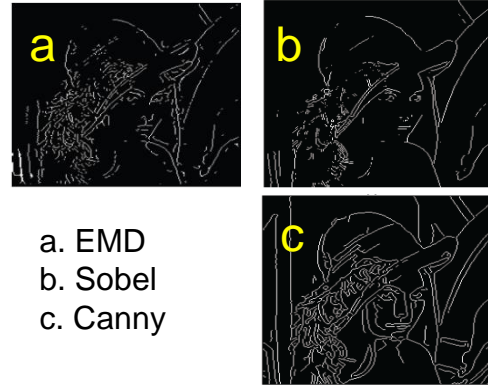
## ❖ Length of day





# Image Processing

- ❖ Edge detection [10]
- ❖ Image denoise [11]
- ❖ Image fusion [12]



Original image 1

Original image 2



Fused image based on average

Fused image based on EMD

image	wavelet	our method
Lena: 52.9715	59.8365	61.1207
Barb: 53.1116	60.3938	61.0224



(a)

(b)



(c)

Figure 3. (a) image with random noise(PSNR=52.9715); (b) wavelet method; (c)the proposed method

image	wavelet	our method
Lena: 31.3933	52.5294	53.1010
Barb: 31.4267	53.0473	53.7436.



(a)

(b)



(c)

Figure 4. (a) image with random noise(PSNR=31.3933); (b) wavelet method; (c)the proposed method

# Problems of HHT

- ❖ P1: Stopping criterion
- ❖ P2: End effect problem
  - ❖ Hilbert Transform
  - ❖ ALIF
- ❖ P3: Mode Mixing
- ❖ P3: Speed of computing

# P1: Stopping Criterion

❖ Standard deviation(SD)  $SD = \sum_{t=0}^T \left[ \frac{|(h_{(k-1)}(t) - h_k(t))|^2}{h^2_{(k-1)}(t)} \right]$  [1]

❖  $SD \leq 0.2 \sim 0.3$

❖ S number criterion Orthogonal Index(OI) =  $\sum_{t=0}^T \frac{C_f C_g}{C_f^2 + C_g^2}$  [2]

❖  $3 \leq S \leq 5$

❖ Three parameter method( $\theta_1, \theta_2, \alpha$ ) [3]

❖ Mode amplitude :  $a(t) = (e_{\max}(t) - e_{\min}(t)) / 2$

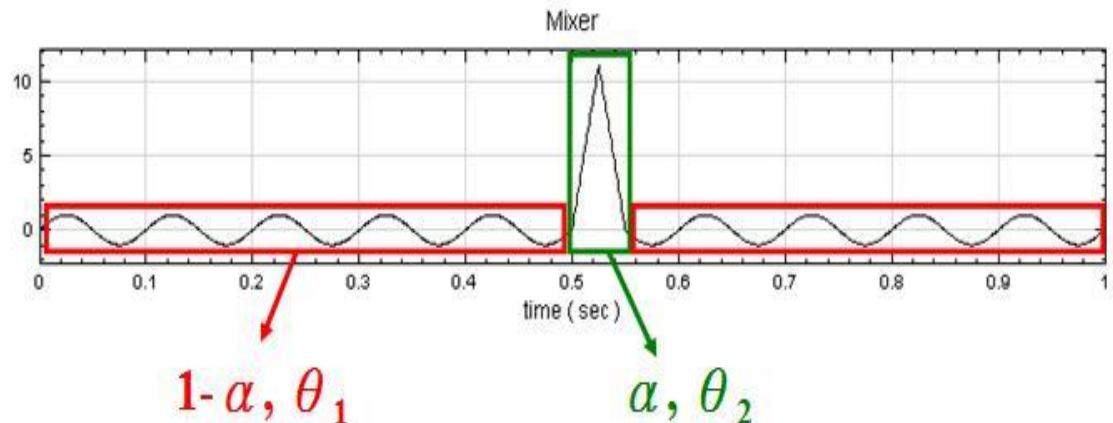
❖ Evaluation function :  $\sigma(t) = |m(t) / a(t)|$

❖  $\sigma(t) < \theta_1$  in  $(1 - \alpha)$

$\sigma(t) < \theta_2$  in  $\alpha$

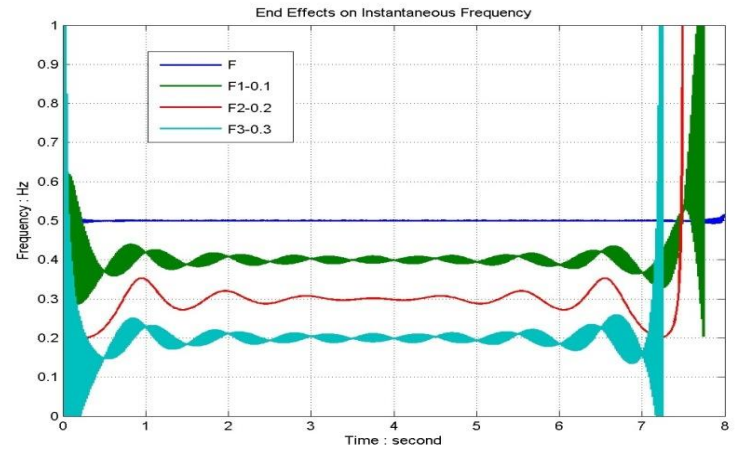
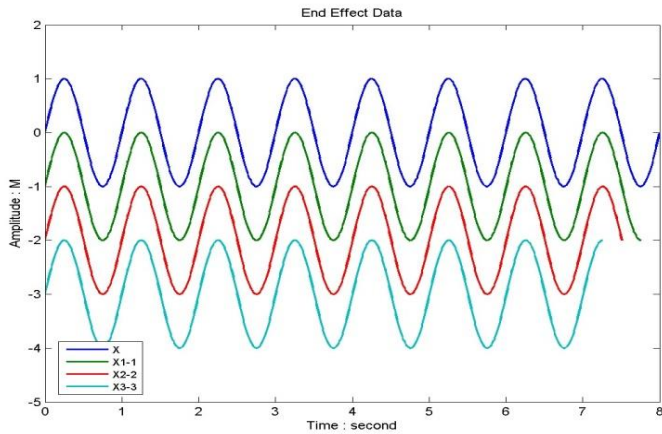
❖  $\alpha \doteq 0.05, \theta_1 \doteq 0.05,$

$\theta_2 \doteq 10\theta_1$



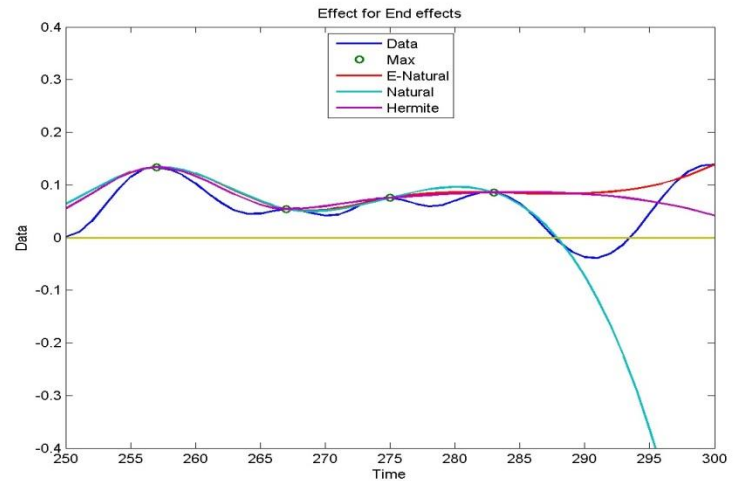
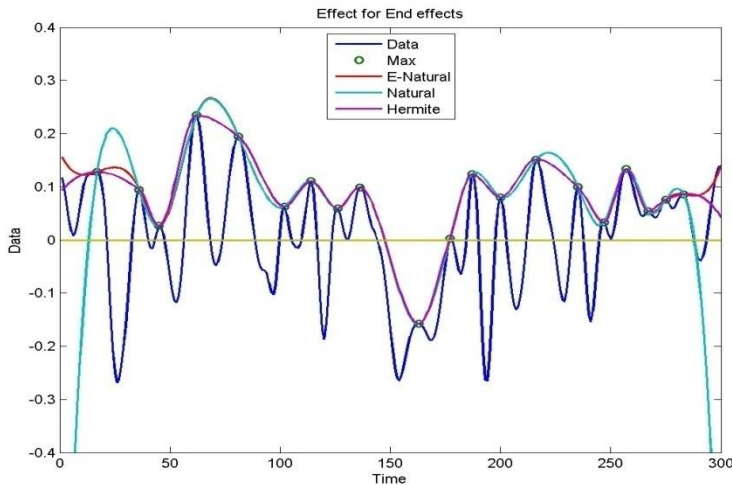
# P2: End Effect Problem

## End effect of Hilbert Transform



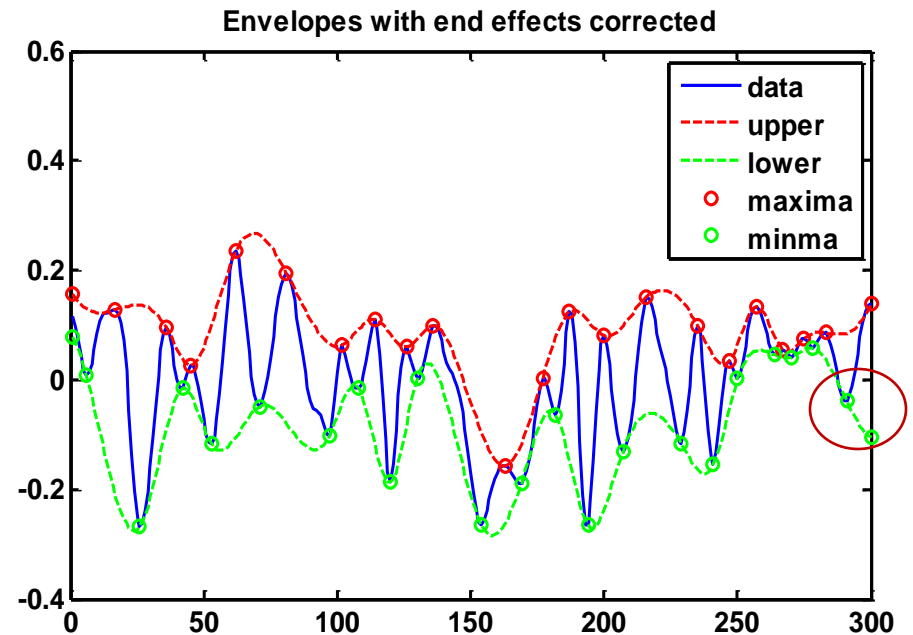
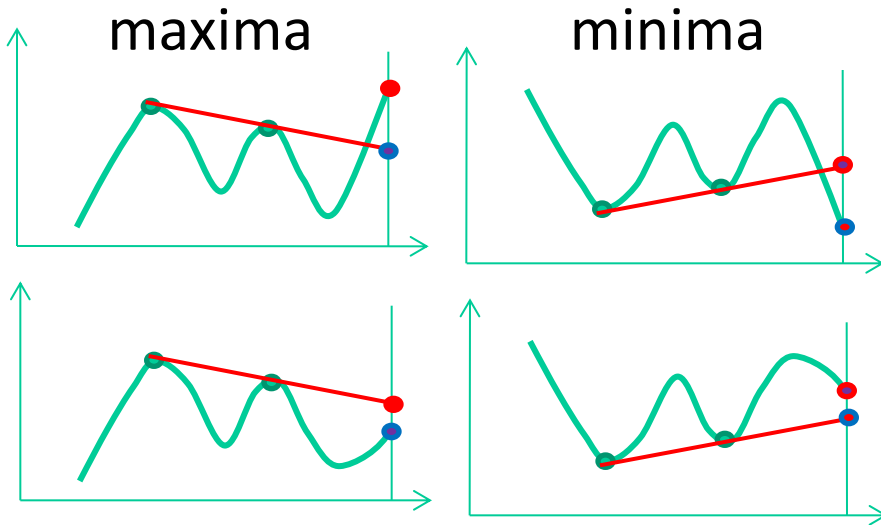
[1]

## End effect of ALIF



# P2: Solutions for End Effects

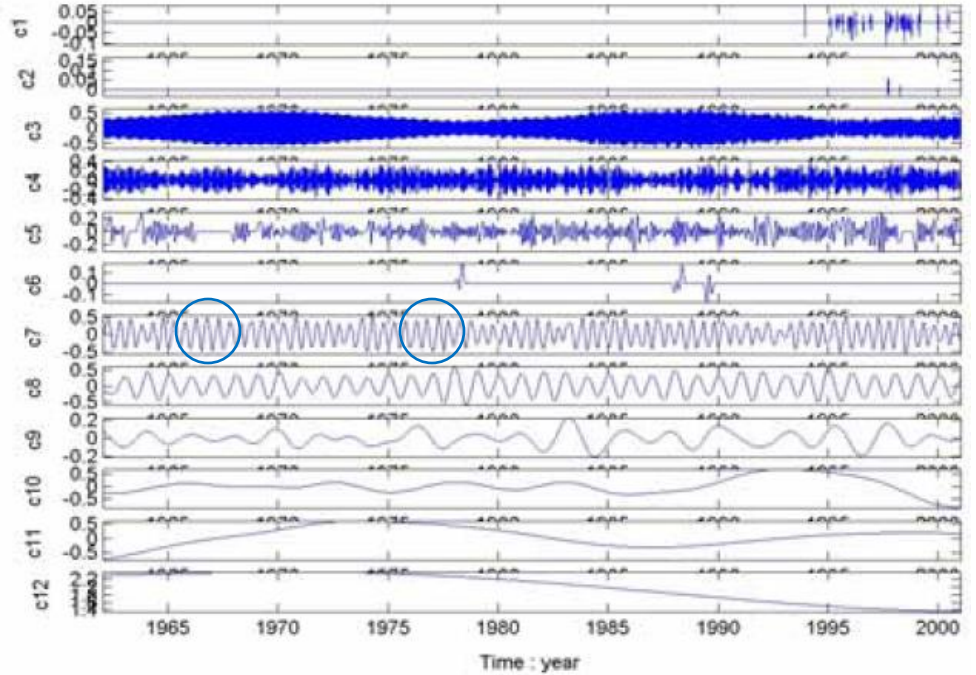
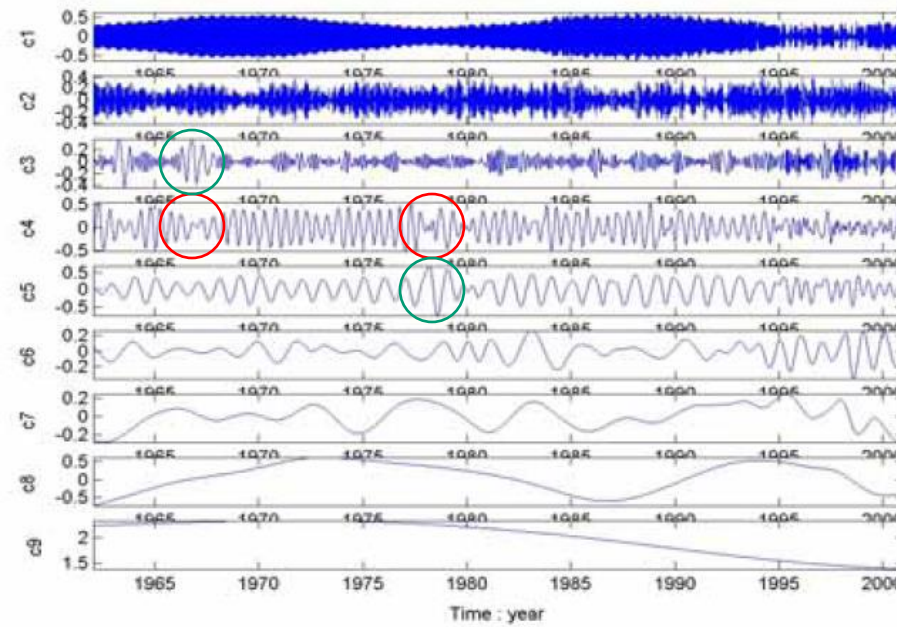
- ❖ End effect of Hilbert Transform
- ❖ Adding characteristics waves
- ❖ End effect of ALIF
- ❖ Extension with linear fittings near the boundaries



# P3: Mode Mixing

IMF LOD CE(average)

IMF LOD62 :  $ci(100,8,8; 3^a; -50,3,3;-1^2,45^a, -10)$



❖ Post-processing of ALIF



# P3: Post-Processing of ALIF

- ❖ Post-processing ALIF can get real IMFs.

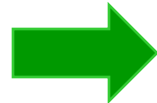
EEMD

$$IMF_1 = \frac{1}{m} \sum_{i=1}^m IMF_{i1}$$

$$IMF_2 = \frac{1}{m} \sum_{i=1}^m IMF_{i2}$$

⋮

$$IMF_k = \frac{1}{m} \sum_{i=1}^m IMF_{ik}$$



Post - processing of EEMD

$$IMF_1 \rightarrow pIMF_1 + residual_1$$

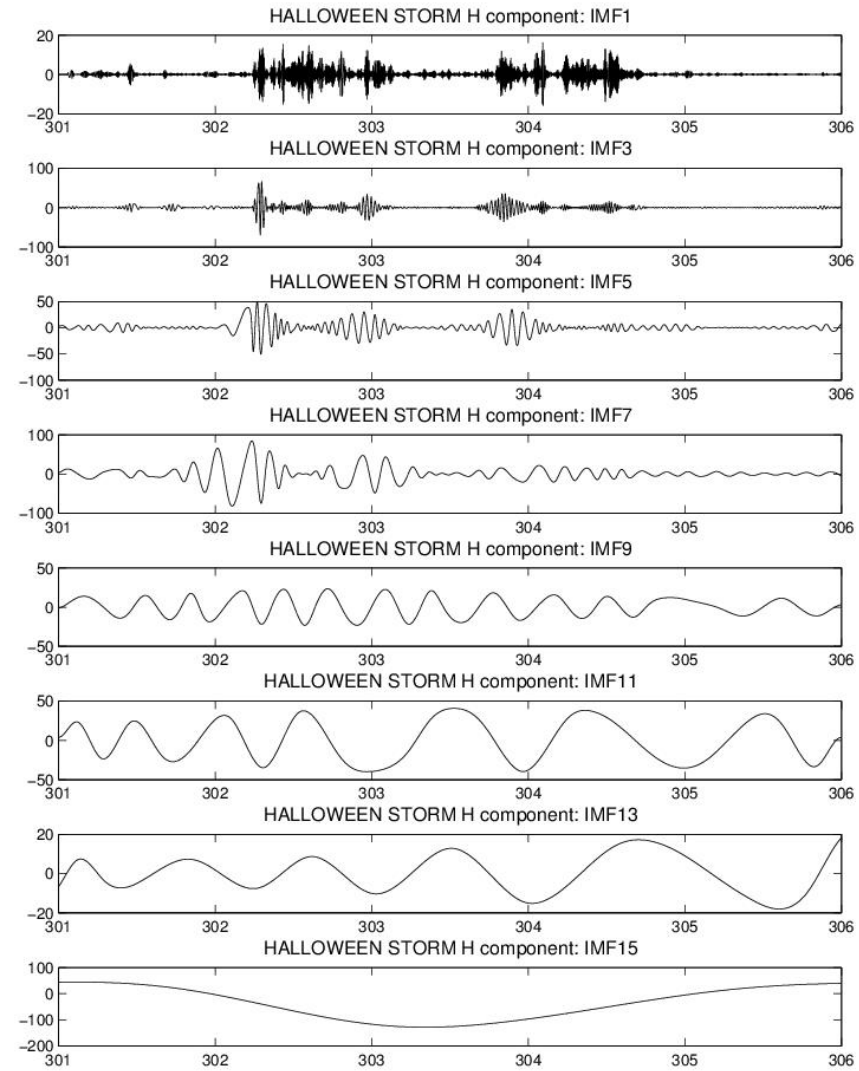
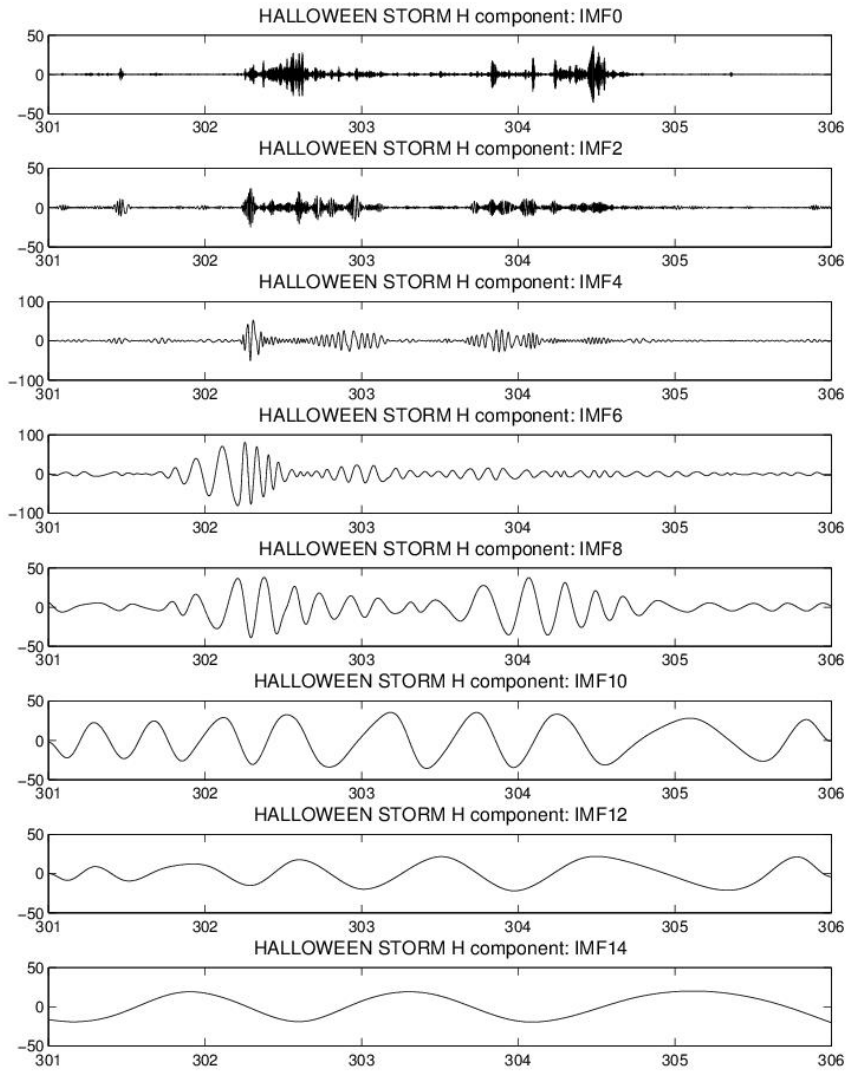
$$IMF_2 + residual_1 \rightarrow pIMF_2 + residual_2$$

⋮

$$IMF_k + residual_{k-1} \rightarrow pIMF_k + residual_k$$

$$\Rightarrow X(t) = \sum_{j=1}^k pIMF_j + trend$$

# Example- Halloween Super Storm





# ALIF – Statistical approach

What is the physical meaning of those components?

Could we sum or partially sum them? What is the way to eventually sum them?

Let's use some statistics;

We developed a test (SMT, Standardized Mean Test) that help us to sum the IMFs

We repeated the same analysis with very quiet days (SSQ;  $K_p \approx 0/0+$ ) in order to identify and detect the physical meaning of the partial sums of the IMFs;

We compared the results obtained at ground to those obtained for magnetospheric observations.

# ALIF – SMT

The basic idea is: if a clear time scale separation exists in a data set  $s(t)$ , this can be divided into two different contributions[Flandrin et al., 2004]:

$$s(t) = \delta s(t) + s_0(t)$$

$s_0(t)$  represents the baseline;  $\delta s(t)$  are the variations around the baseline.

IDEA:  $\delta s(t)$  has the following characteristics:

1. has close to zero standardized mean ( $\mu/\sigma$ );
2. represents the fluctuating/oscillatory contribution to the time series  $s(t)$ .

# ALIF – SMT

Using the orthogonality and completeness properties of EMD, we define  $\delta s(t)$  as the reconstruction of a subset of the first  $k$  empirical modes (IMF –  $c_j$ ) which satisfies the previous two properties, that is:

$$\delta s(t) = \sum_{j=1}^k c_j$$

$k$  is the last IMF ( $c_j$ ) for which  $\delta s(t)$  has  $\mu/\sigma \approx 0$ .

# ALIF – Halloween 9

AQU:  $\lambda$

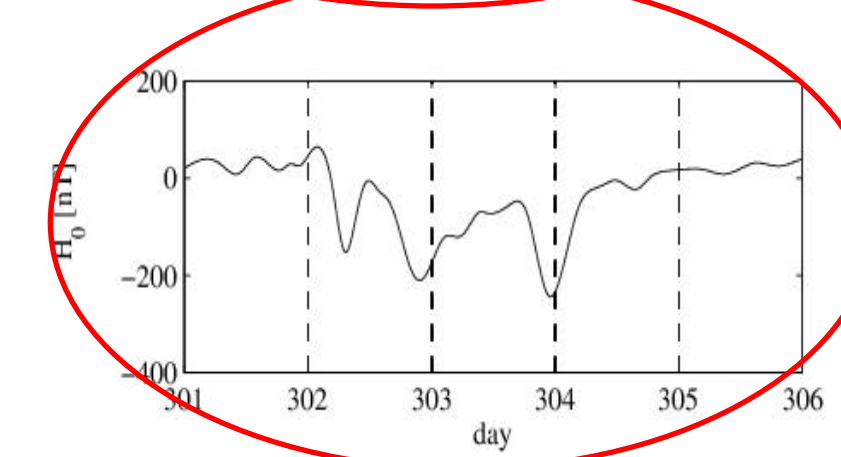
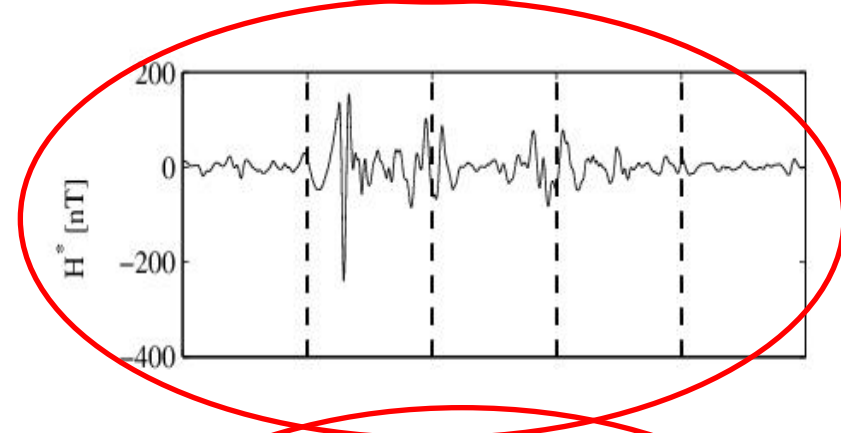
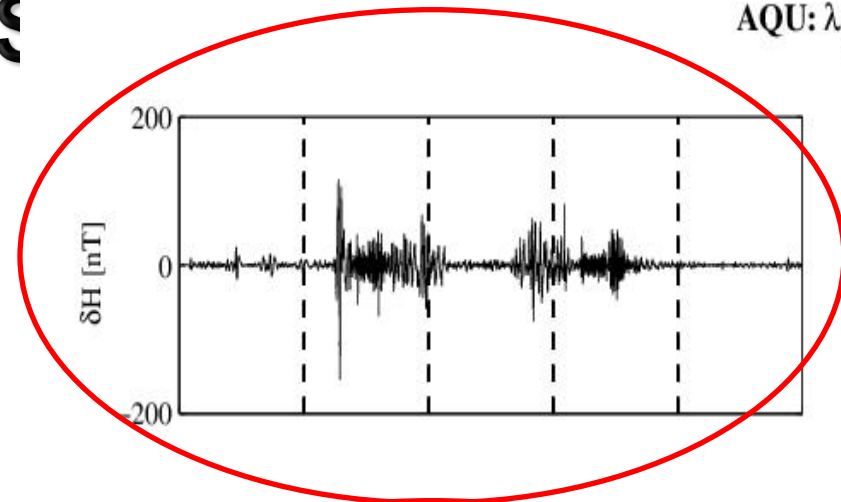
Repeating the same analysis for the HGS:

The SMT applied to the EMD gives 3 contribution at AQU e 2 contributions at both GOES.

$H^*(t)$  gives a representation of the ionospheric contribution. It lacks in the magnetospheric reconstruction and presents characteristics periods between 6-24 h.

$H_0(t)$  during a GS shows the typical behaviour of a storm: a SI followed by a Main Phase and a Recovery Phase.

$\delta H$  are the high frequency fluctuations, related to the turbulent character of the SW.



# ALIF – MSA

For each IMF we evaluate the PDF ( $p(IMF)$ ), probability distribution function, with a defined binning ( $n_{bin} = \sqrt{t_c}$ , Flandrin et al., 2004; Materassi et al., 2009; Piersanti et al., 2016).

The STD, the excess of Kurtosis ( $K_{ex} = K - 3$ ) e the Skewness was evaluated;

The relative ( $\epsilon_{rel}$ ) e the Shannon Information ( $I$ ) was evaluated:

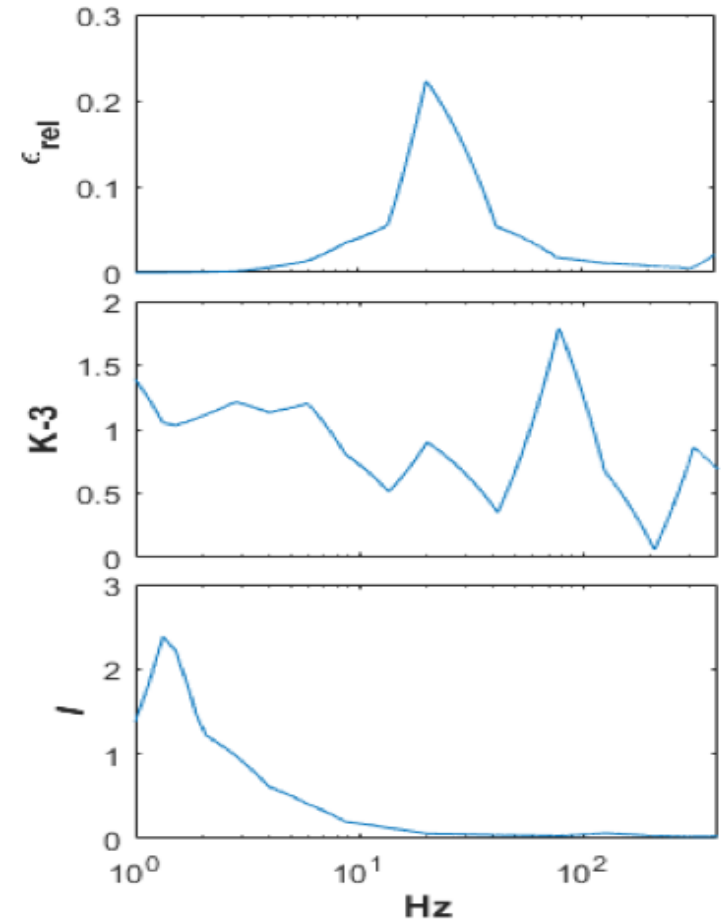
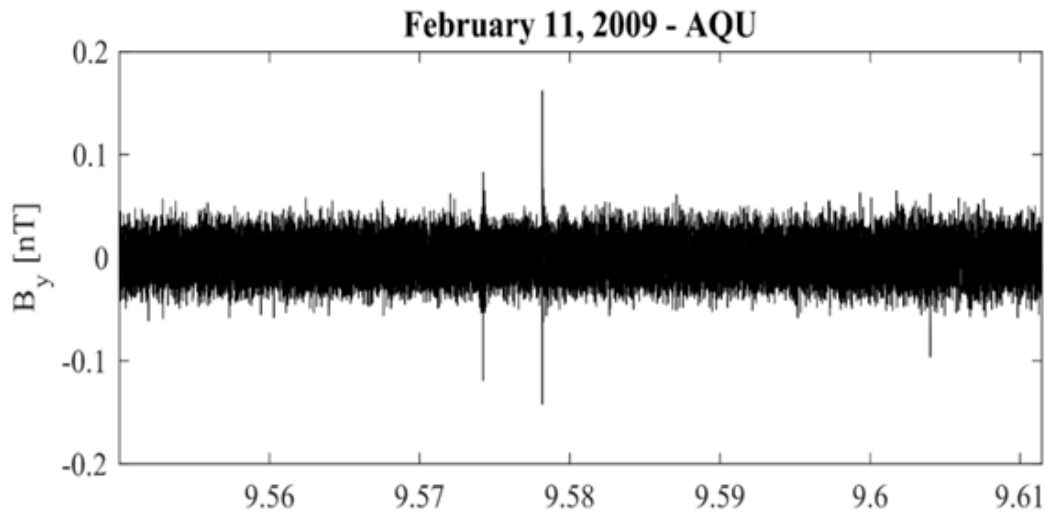
$$\epsilon_{rel} = \frac{\int_s |IMF_k(t)|^2 dt}{\int_s |s(t)|^2 dt}$$

$$I = - \sum_{\{IMF_k\}} p(IMF_k) \cdot \log_2 p(IMF_k)$$

# ALIF – MSA – Example DEMETER EFD

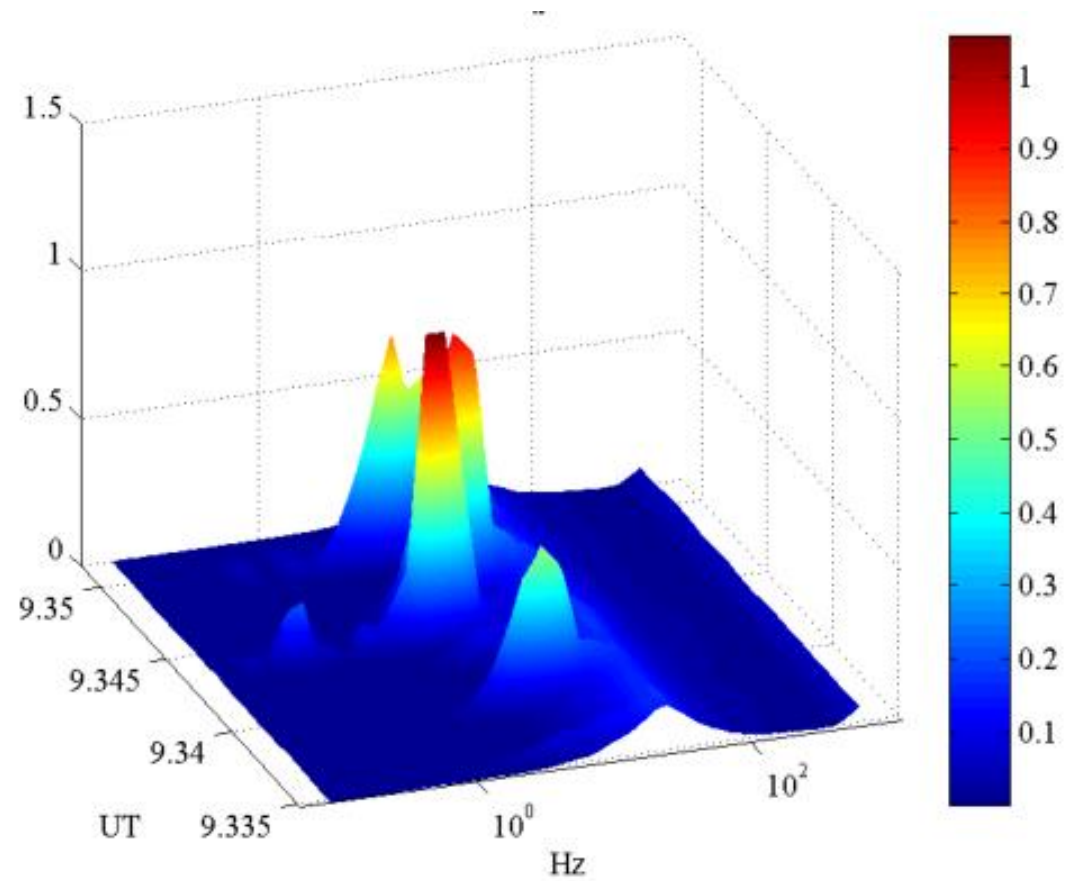
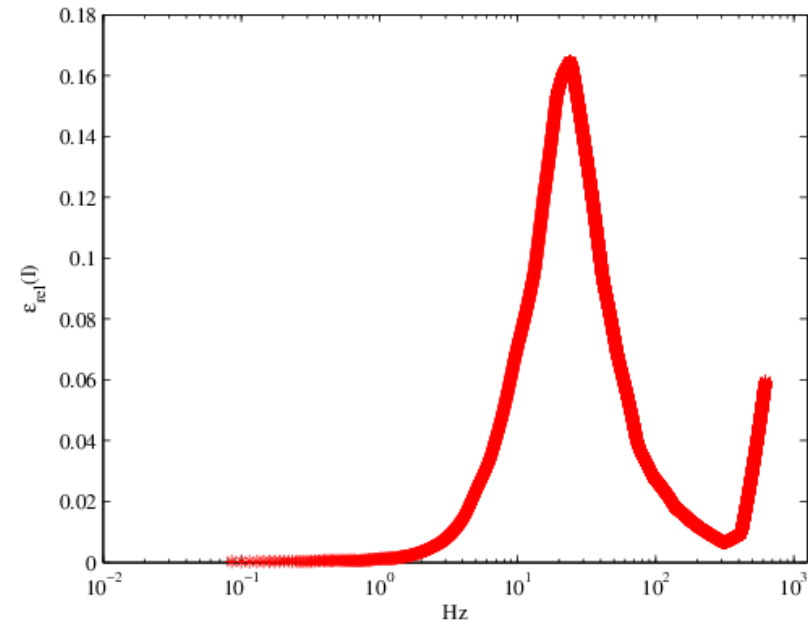
Since:

1. Kex measure how abundant are the rare fluctuation at different frequencies;
2. I measure the «casual degree» for each scale (for each frequency).



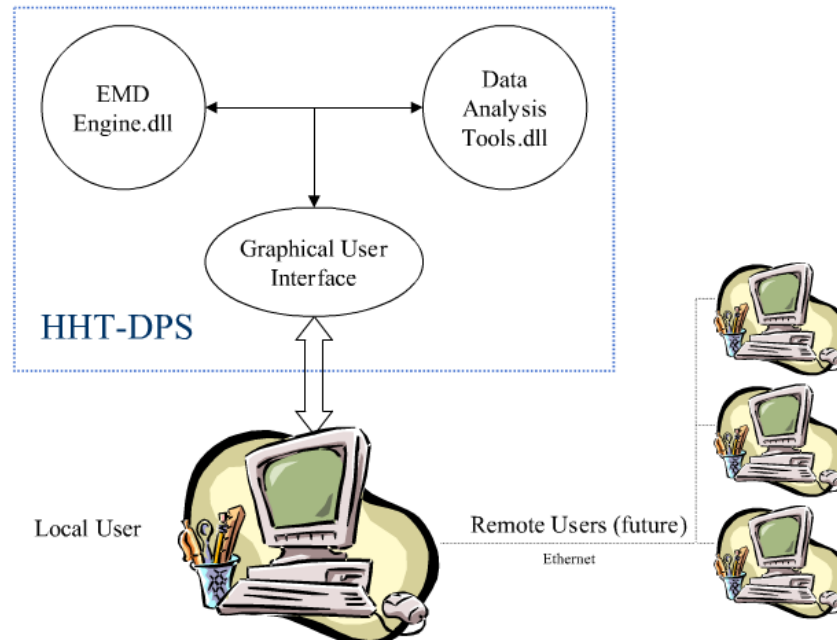
# 3D RELATIVE ENERGY

Multi-scale statistics via IF - B<sub>x</sub> Component



# P4: Speed of Computing

- ❖ The processing time of HHT is dependent on complexity of the data and criterions of the algorithm
- ❖ HHT data processing system(HHT-DPS)
- ❖ Implementation of HHT based on DSP [13]





# Conclusion

- ❖ The definition of an IMF guarantees a well-behaved Hilbert transform of the IMF
- ❖ IMF represents intrinsic signature of physics behind the data
- ❖ Although there are still many problems in HHT, HHT has lots of applications in all aspects

Thank you