Nonlinear waveform reconstruction study Higher-Order Spectral Analysis (HOSA)

## Andrea Cesarini

European Gravitational Observatory (EGO), Cascina, Pisa, Italy


## Study

## Aim:

Searching for a nonlinear approach for waveform transient signal reconstruction

## Supervisor:

Dr. Elena Cuoco

## Internship:

Data and Noise Analysis Group

## Generalizing spectral analysis

## "Cumulants are combination of moments"

1st-order

$$
c_{1}(\tau)=\mathrm{E}[x(t)]
$$

mean
2nd-order
correlation
spectrum

$$
c_{2}(\tau)=\mathrm{E}\left[x^{*}(t) x(t+\tau)\right]
$$

$$
P(f)=\int_{-\infty}^{\infty} c_{2}(\tau) e^{-j 2 \pi f \tau} d \tau
$$

The statistics of a
Gaussian signal is completely described by using its Ist- and its 2ndorder statistics
Fourier transform of the autocorrelation

3rd-order $\quad c_{3}\left(\tau_{1}, \tau_{2}\right)=\mathrm{E}\left[x^{*}(t) x\left(t+\tau_{1}\right) x\left(t+\tau_{2}\right)\right]$ triple correlation
$\begin{aligned} & \text { bispectrum } \\ & \end{aligned} B\left(f_{1}, f_{2}\right)=\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c_{3}\left(\tau_{1}, \tau_{2}\right) e^{-j 2 \pi\left(f_{1} \tau_{1}+f_{2} \tau_{2}\right)} d \tau$
2nd-order Fourier transform

## Higher-Order Spectral Analysis (HOSA)

Higher-order statistics do not maintain memory of gaussianity (filtering).

## Higher-order spectral analysis (HOSA)

## Generalized (non Gaussian) signals



The spectral density is a function of frequency and not a function of time. However, the spectral density of small "windows" of a longer signal may be calculated and plotted versus the time associated with the window. The figure shows the variations in the accuracy and reliability of these techniques (Subramanian, 1990).

- Gaussian noise suppression
- Study of dataset quasi-Gaussianity
- Nonlinear frequency coupling

Higher-order cumulants (>2) of pure Gaussian signals are zero and contain redundant information about the deterministic portion of the signals.


In real cases when signals are heavily corrupted, averaging the redundant information is possible to treat the noise.

Phase coupling associated with nonlinearities cannot be correctly identified

## Bispectrum Analysis

## Discrete time treatment

Bispectrum redundant information

(iii) $\tilde{T}_{p, q}^{(3)}=\left[\tilde{T}_{-p,-q}^{(3)}\right] *$ if $T(x)$ is real.

- Bispectrum symmetries of a band-limited signal.
- For a real signal the bispectrum is completely determined by a single octant (blue).
- For a complex signal the symmetry relation (iii) is not applicable and a second octant is necessary in order to determine the bispectrum (red).

Stationarity vs. Nonstationarity


- The isosceles triangle (blue) is a consequence of the stationary and real signal and the symmetry properties.
- A nonzero extra triangle (pink) is a direct consequence of nonlinearity.


## Bispectrum Analysis (2)

## Indirect bispectral estimate

In practical cases (time-limited and band-unlimited signals), the bispectrum is computed by using the Fourier transform of the triple correlation (indirect estimate). The estimated cumulant is convolved by a 2D window function in order to obtain an improved estimation for the bispectrum of the signal.

Several windowing functions have been developed. Here we test the Parzen, the Sasaki and the Mean Squared Error (MSE) optimal Rao-Gabr windows.

| io io | Window | Index |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | J | V | B | E |
|  | Daniell | 99468.5 | 0.1199 | 8990 | 1078.5 |
|  | Parzen | 8392.43 | 0.0409 | 1324.78 | 54.2 |
| - | Hamming | 60664.8 | 0.9067 | 6261.80 | 567.76 |
|  | Priestley | 288002 | 0.2032 | 10909.3 | 2216.91 |
|  | Sasaki | 1315.2 | 0.0486 | 2007.43 | 97.29 |
|  | MSE optimal | 2220.74 | 0.0691 | 458.69 | 31.68 |
|  | Rao-Gabr O | timal wind |  |  |  |

## bias~J <br> variance~V

MSE~E=VxB

## Bispectrum Analysis (2)

None


Windowing: $\sin 10 \mathrm{~Hz}-30 \mathrm{~Hz}$



Sasaki

Optimal window (MSE)


## Bispectrum Analysis (3)



## Bispectrum Analysis (4)

Windowing Rao-Gabr: SGIOHz+white at low SNR (<0.6)


## Signal extraction/filtering/reconstruction

Testing
Filtering Frequency-domain via DCT
D.V.Fevralev et al., 2006,"Combined bispectrum-filtering technique for signal shape estimation with DCT-based adaptive filter"
D.V.Fevralev et al., 2006,"Signal shape reconstruction by DCT-based filtering of Fourier spectrum recovered from bispectrum data"

# Robust Amplitude and Phase reconstruction algorithm 

G.Sundaramoorthy, 1990, "Bispectral Reconstruction of Signals in Noise Amplitude Reconstruction Issues"
M.Nakamura, I993,"Waveform Estimation from Noisy Signals with Variable Signal Delay Using Bispectrum Averaging"

## To be coded Inverse Filtering

M.Pulakka et al., 2005, "A Toolkit for Voice Filtering and Parametrisation"
J.Walker, 2003,"Application of the Bispectrum to Glottal Pulse Analysis"

## HOSA Integration

## Traditional (stationary) approach



## HOSA Integration (2)

Traditional (stationary) approach


## Advanced (stationary and nonstationary) approach



## HOSA Integration (4)

## Advanced (stationary and nonstationary) approach



## HOSA Integration (5)

## Signal-to-Background estimate



## HOSA Integration (6)

## Nonstationary nonlinear correlations of frequency lines

- Nonlinear correlation test
- Prompt data monitoring for nonstationary nonlinear coupling in the frequency-domain
- Search for multi-channel nonlinear coupling of events produced by:
-> Gravitational wave
-> Laser fluctuation
-> Electromagnetics
-> Seism
-> Thermal noise



## What next...

- Test on real data
- Modify for suiting performance of an in-time analysis
- Integrate it as tool on NMAPI framework


## End

