Glitchology: an Elementary Perspective

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Outlook

- Glitch Busting
- Assembling Glitch Databases
- Glitch Enthomology
- Glitchy Noise Modeling
- A Simple, Physically Driven Model
- Proto Glitches, PCA, and Beyond
- Ongoing Work

Gitches

Transient disturbances of environmental (exogenous, e.g. lightning) and/or instrumental (endogenus, e.g. laser) origin;

Appear *ubiquitously* in the data gathered by interferometric GW detectors, with a *wide range* of energies;

Idiosyncratic signals: exhibit a *wide variety of shapes*; still mostly visually *similar* and *erratically recurrent*.

Glitch *rate* roughly inversely proportional to glitch *strength*;

Important impact on instrument's noise (*non-stationarity, heavy-tails*) -> glitches *spoil* naïve (Gaussian) detectors.

… word comes from Yiddish term גליטש

Glitch Sources

"External"
- Seismic activity
- Acoustic noise of various origin
- Electric/magnetic surge

Structural"
- Vacuum pipe expansion/contraction (stepwise)

"Sub systems"
- Laser control system
- Thermal compensation system
- Cavity alignment

instability, back-lash, saturation

"sensors/ actuators"
- Piezo driver malfunction
- Sensor/actuator malfunction
- Digital circuitry noise

Residual (unknown origin)

[J. Aasi et al., Class. Quantum Grav. 29 (2012) 155002]

Glitchology Goals

- Tracing out the *origin* of *typical* glitches families, and tweaking the machine design so as to *suppress* or *mitigate* them;

- Identifying surviving glitches in the GW channel, capitalizing on information from the instrumental / monitoring channels, and tagging/vetoing the data appropriately ;

- Characterizing statistically the *residual* glitchy noise, and devising robust detection algorithms (noise modeling).

- Subtracting identified glitches from the GW channel (noise cancellation);

LIGO/Virgo References

A. DiCredico et al., “Gravitational Wave Burst Vetoes in the LIGO S2 and S3 Data Analysis,” Class. Quantum Grav. 22 (2005) S1051.

L. Blackburn et al., “Monitoring Noise Transients During the Fifth LIGO Science Run,” Class. Quantum Grav. 25 (2008) 184004.

N. Christensen et al., “LIGO S6 Detector Characterization Studies,” Class. Quantum Grav. 27 (2010) 194010.

F. Acernese et al., "Noise Studies During the First Virgo Science Run and After," Class. Quantum Grav. 25 (2008) 184003.

M. Del Prete et al., "Characterization of a Subset of Large Amplitude Noise Events in VIRGO Science Run 1 (VSR1)," Class. Quantum Grav. 26 (2009) 204022 .

J. Aasi et al., "The Characterization of Virgo Data and its Impact on Gravitational Wave searches,“ Class. Quantum Grav. 29 (2012) 155002.]

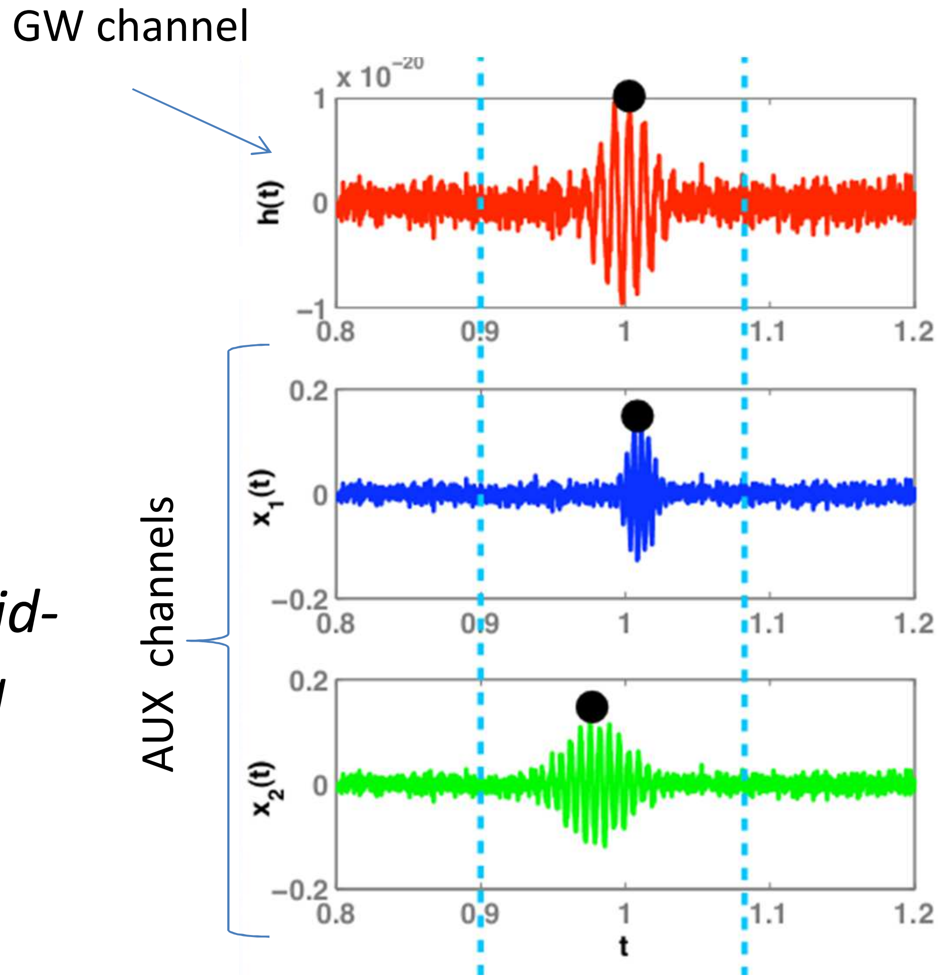
etc.

Old Style Vetoing

Check whether a trigger in the GW channel is ***coincident in time*** with a trigger in one (or more) AUX channel(s), *at a given significance level.*

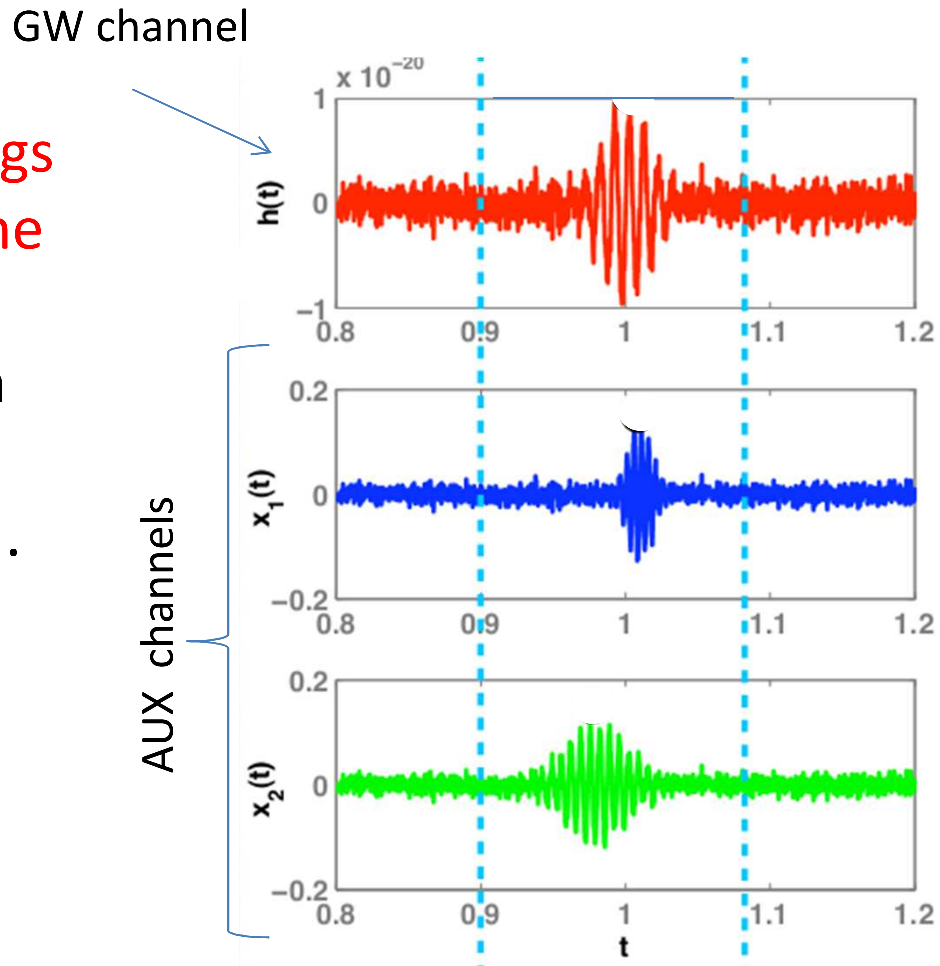
(characterize preliminarily *accid-ental coincidence statistics via* time slide experiments).

[K.C. Cannon, LIGO P070085]



(markers identify peak-times)

Improved Vetoing



Use knowledge of the couplings (*transfer functions*) between the AUX channels and the GW one to check ***consistency*** between transients occurring in the GW and the instrumental channels .

Better efficiency, lower rate of accidental vetos.

[P. Ajith et al., PRD 76 (2007) 042004].

Data Quality

Category	Definition	Prescription for analyses
CAT1	Flags obvious and severe malfunctions of the detector	Science data are redefined when removing CAT1 segments. Offline analysis pipeline should run on data only after removing CAT1 time periods
CAT2	Flags noisy periods where the coupling between the noise source and the GW channel is well established	Triggers should be removed if flagged by a CAT2 veto. A significant trigger surviving the CAT2 vetoes is a good candidate for detection follow-up
CAT3	Flags noisy periods where the coupling between the noise source and the GW channel is not well established	CAT3 vetoes should not be applied blindly. Triggers flagged by a CAT3 veto should be followed up carefully. CAT3 vetoes are applied to compute upper-limits
CAT4	Flags time periods where hardware injections were performed	Periods flagged by a CAT4 veto are used for specific studies. This category is applied for any search analysis
CAT5	Advisory flag to keep track of problems for which no (or very low) impact was seen in the GW channel	CAT5 are only used at the last stage of the detection follow-up. The validity of the flagging must be carefully checked by experts.

[F. Robinet et al., Class. Quantum Grav. 29 (2011) 155002]

DQ Figures of Merit

d = *Dead-time* (DQ-flagged fraction of science time)

UP = *Usable-percentage* (fraction of DQ segs used to flag at least one trigger)

ε = *Efficiency* (fraction of triggers which are flagged)

BURST	CAT1	CAT2	CAT3	KW vetoes
UP, $SNR > 5$	75.5 %	87.5 %	73.1 %	91.2 %
	CAT1	**CAT1+2**	**CAT1+2+3**	**CAT1+2+3+KW vetoes**
d	0.8 %	5.0 %	8.1 %	8.2 %
ε, $SNR > 5$	1.2 %	16.5 %	22.6 %	24.2 %
ε, $SNR > 8$	5.4 %	61.8 %	74.6 %	76.3 %
ε, $SNR > 15$	23.8 %	86.4 %	88.6 %	89.2 %

$\varepsilon/d = 1$ $\Leftrightarrow$ flag is basically *random;* $\varepsilon/d > 1 \Leftrightarrow$ flag deemed as *effective*;

A (Poissonian) probability of rejecting a true GW signal is attached to each DQ

[F. Robinet et al., Class. Quantum Grav. 27 (2010) 194012]

Popular Wisdom

We should refrain from
throwing the baby out with the bath water…

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GW Interferometer Noise

Appears to consist of three basic components:

$$n(t) = n_{NB}(t) + n_g(t) + n_{res}(t)$$

Narrowband component

"strong" (discernible) gitches

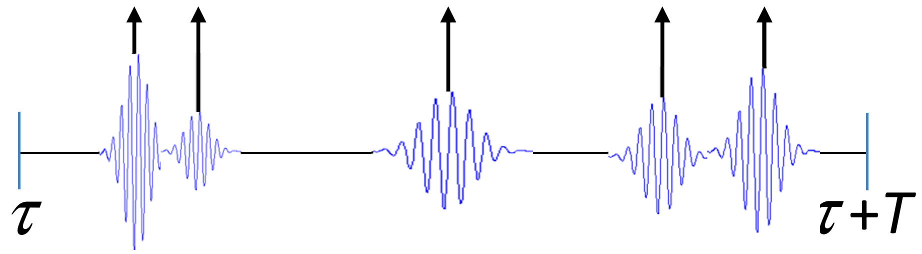
***residual* (floor) component**
Besides the "good" expect-ed Gaussian component, it may contain a *locally* Gaussian but *breathing.* (slowly fluctuating variance)

None of these terms is described by a Gaussian - stationary distribution !

Naïve detection estimation algorithms based on a Gaussian Stationary noise-model will underperform !!

Simulating Glitch Noise

Let :



$\Theta = [\tau, \tau + T]$ the time window ;

λ_Θ the glitch *firing-rate*; may fluctuate adiabatically (Cox process)

K_Θ the random, (Poisson distributed, Hurwitz-Kač th.) no. of glitches in Θ :

$$prob[K_\Theta = K] = \frac{(\lambda_\Theta)^K \exp[-\lambda_\Theta]}{K!}$$

$\{t_\Theta{}^{(k)} \mid k = 1 \dots K_\Theta\}$ a set of K_Θ random i.i.d. (uniform) firing times in Θ;

$\psi(t, \vec{a})$ an elementary generic transient waveform (*atom)* whose *shape* is set by the (vector) parameter $\vec{a} = \{a_1, a_2, \dots, a_N\}$;

$\{\psi(t - t_\Theta{}^{(k)}; \vec{a}^{(k)} \mid k = 1 \dots K_\Theta\}$ a set of atoms, with $\{\vec{a}^{(k)} \mid k = 1 \dots K_\Theta\}$ a set of random parameters (with known distributions)

[M. Principe and I. Pinto, Class. Quantum Grav. **25** (2008) 075013]

A Glitchy Noise Model

The resulting stochastic process (generalized shot noise) has been introduced by David Middleton [D Middleton IEEE T-EMC-21 (1979) 209].

$$n_g(t \in \Theta) = \sum_{k=1}^{K_\Theta(\Theta)} \psi(t - t_\Theta{}^{(k)}; \tilde{a}_\Theta{}^{(k)})$$

Its characteristic functions in additive N(0,σ) noise can be computed to *any* order [D. Middleton, J. Appl. Phys. 22 (1951) 1143], e.g.

$$F^{(1)}(\xi) = \exp\left\{\lambda\Theta\{\langle\exp[\iota\xi\psi(t-\tau;\vec{a})]\rangle_{(\tau;\vec{a})} - 1\} - \frac{\sigma^2\xi^2}{2}\right\}$$

Its PDF is also well approximated by a mixture of (a few) Gaussians with zero mean and different standard deviations.

[M. Principe and I. Pinto, Class. Quantum Grav. **25** (2008) 075013]

A Glitchy Noise Model, contd.

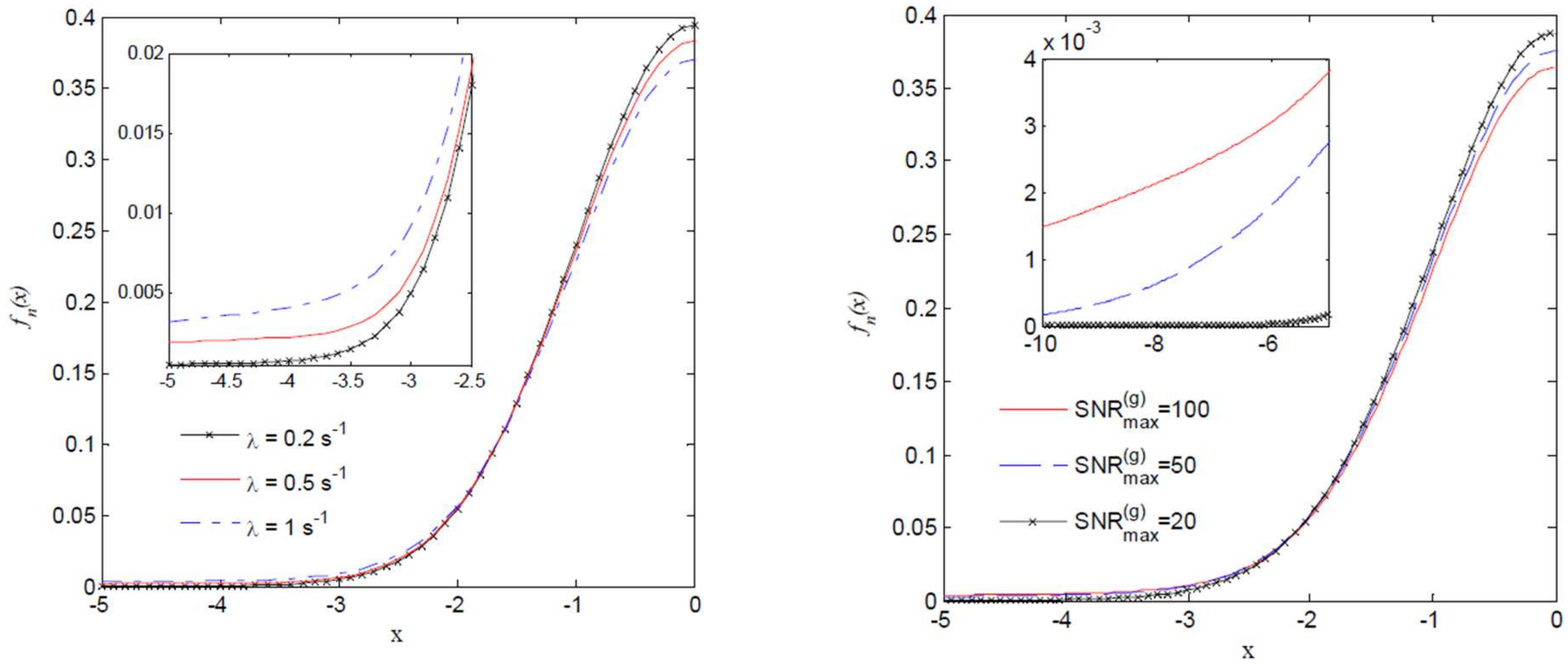
The statistical properties of the above glitchy noise model depend mainly on *a few gross parameters*: the product between the (local) glitch-rate $\bar{\lambda}_T$ and the typical glitch time-width Δ_ψ, and the *glitch contrast* against the residual (Gaussian) noise

Strong glitches (which are *detectable* against the residual noise floor) occur with typical rates such that $\bar{\lambda}_T \Delta_\psi \leq 1$. Their effect is making the noise distribution *heavy-tailed*.

Weak (undetectable) glitches occur at relatively *high rates*. In the limit where $\bar{\lambda}_T \Delta_\psi \gg 1$, one can show that the glitch noise distribution *becomes Gaussian, irrespective of the individual glitch shapes* . High-rate weak glitches may originate the observed (slowly) non-stationary locally-Gaussian component, as an effect of (slow) fluctuations in $\bar{\lambda}_T$ (Cox process).

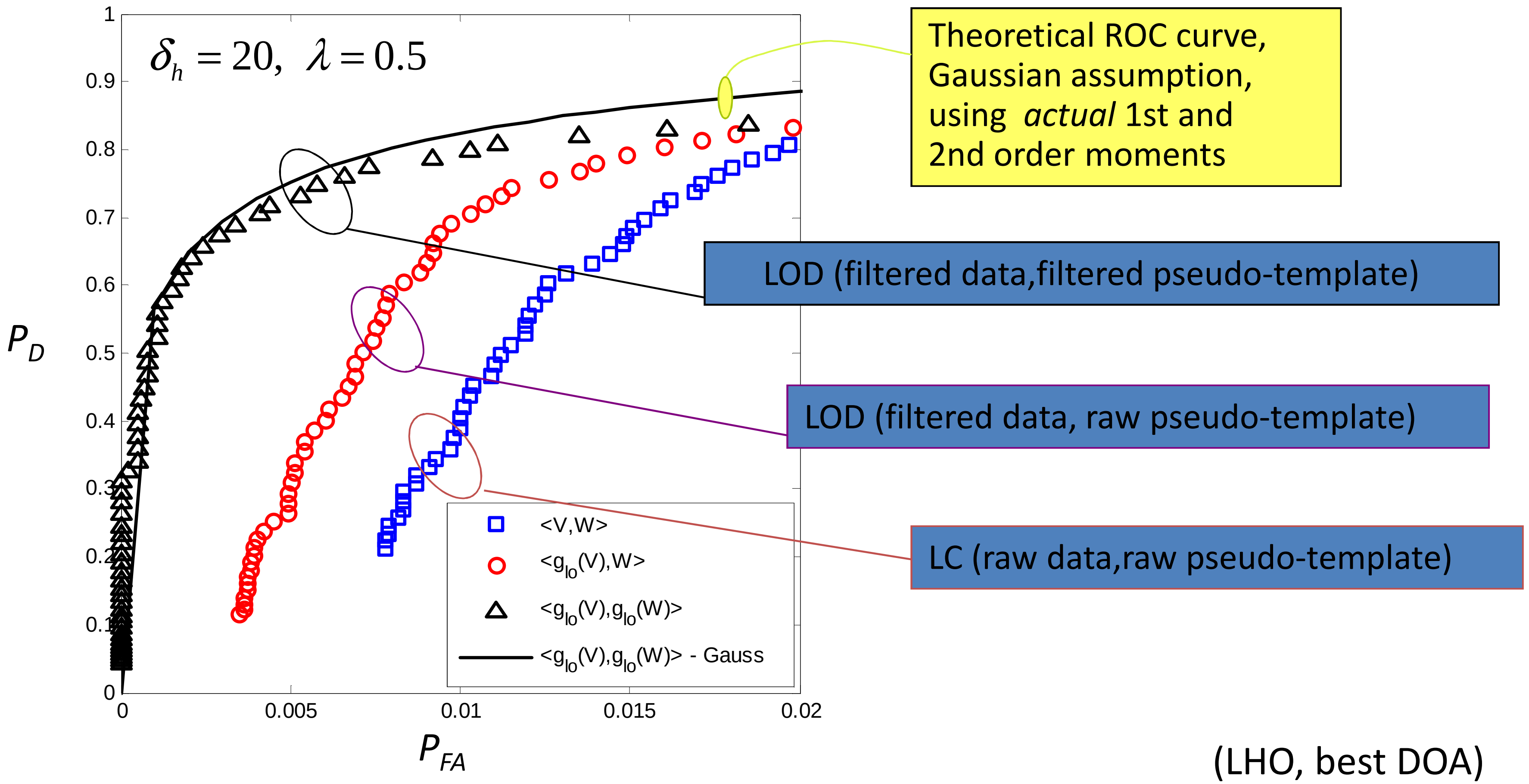
[M. Principe and I. Pinto, Class. Quantum Grav. **25** (2008) 075013]

A Glitchy Noise Model, contd.



Robust algorithms for the detection of unmodeled GW transients in a network of (non-colocated) interferomers affected by glitchy noise have been discussed in [M. Principe and I. Pinto, LIGO-P1000134; expanded version subm. to PRD, 2014] Based on robust implementations of the locally optimum network likelihood ratio.

Improvement over LC



(LHO, best DOA)

Roadmap

DONE

- Validate a quick reliable procedure for extracting training sets of "clean" glitches from (long) time series . **Key problem: robustness** .

- Investigate "fine structure" of glitches (look for evidences of the fact that, in general, glitches are "multi-component") ➡ **skeleton representations .**

- Investigate glitch (linear) decompositions using a *pre-determined* set of elementary "glitches". Simplest choice: SG-atoms ➡ **Matching - Pursuit representation of glitches using a Gabor-atom dictionary** .

- Investigate glitch (linear) decompositions using an **adaptively - determined** set of elementary glitches ➡ **Basis - Pursuit, K-means-SVD dictionary construction**

⬇

Estimate-and-subtract "strong" glitches from time series (BSS)
➡ **reduce vetoed fraction**

⬇

Improve generalized shot-noise model of (*residual*) glitchy noise component
(improve noise characterization)

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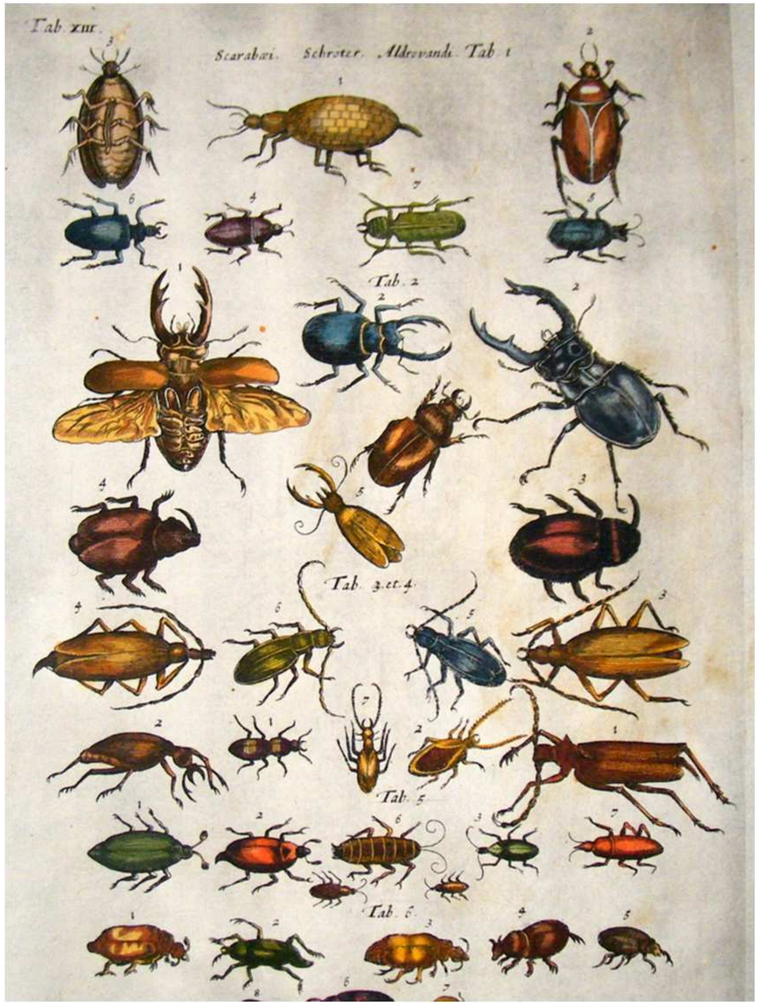
Enthomology

Enthomology: the study and understanding (Greek: λογία) of the insects (Greek: ἔντομοι), literally "entities that consist of (several) parts"



Glitch Enthomology Goals

Shedding light on the *fine-structure* of noise glitches, in preparation of their *classification*

Identifying *multi-component* glitches, and isolating their *constituents*, so as to (hopefully) check back their physical origin;

etc (see roadmap) …1

TF Representation Tools

Natural choice for analyzing non-stationary (transient) signals;

All limited by Gabor *resolution bound* (frequency · time uncert-ainty) - to different extents, e.g.,

Short-Time Fourier Transform (*worst* of them all in terms of TF resolution);

Non-uniform TF-tiling linear transforms, including wavelet (e.g., Kleine-Welle, L. Blackburn, LIGO-T060221 etc), and constant-Q (e.g., Q-pipeline, S. Chatterji, LIGO-G060044 etc) transforms;

Wigner-Ville transform, *best* (in energy-preserving transform class) in terms of resolution …

… but, being bi-linear, exhibiting signal-signal and signal-noise *intermodulation artifacts* which may affect its readability

TF Representation Tools, contd.

Atomic Decompositions

[**A. Altheimer, LIGO G0900045; M. Princip, CQG 26** (2009) 045003 **,**
N. Cornish and T. Littenbergh LIGO-P1000084]

Hilbert-Huang Transform

[A. Stroer et al., Class. Quantum Grav. 28 (2011) 155001;
Phys. Rev. D79 (2009) 124022]

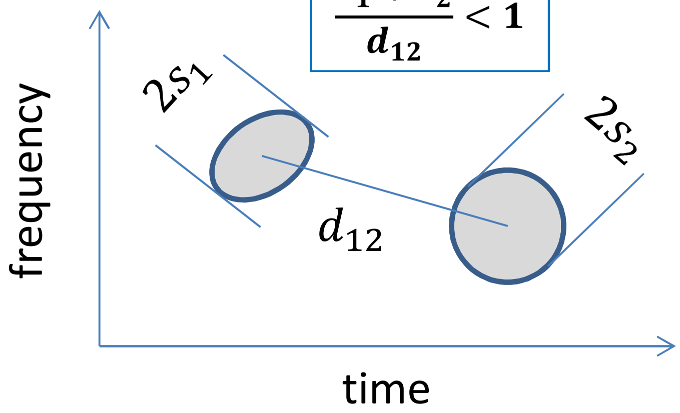
Multi Component Signals

Signals can be "decomposed", in principle, *in an infinite number of ways* into a finite or infinite number of "components".

Meaningful definitions should identify multi-component signals such that their components have *different physical origins*.

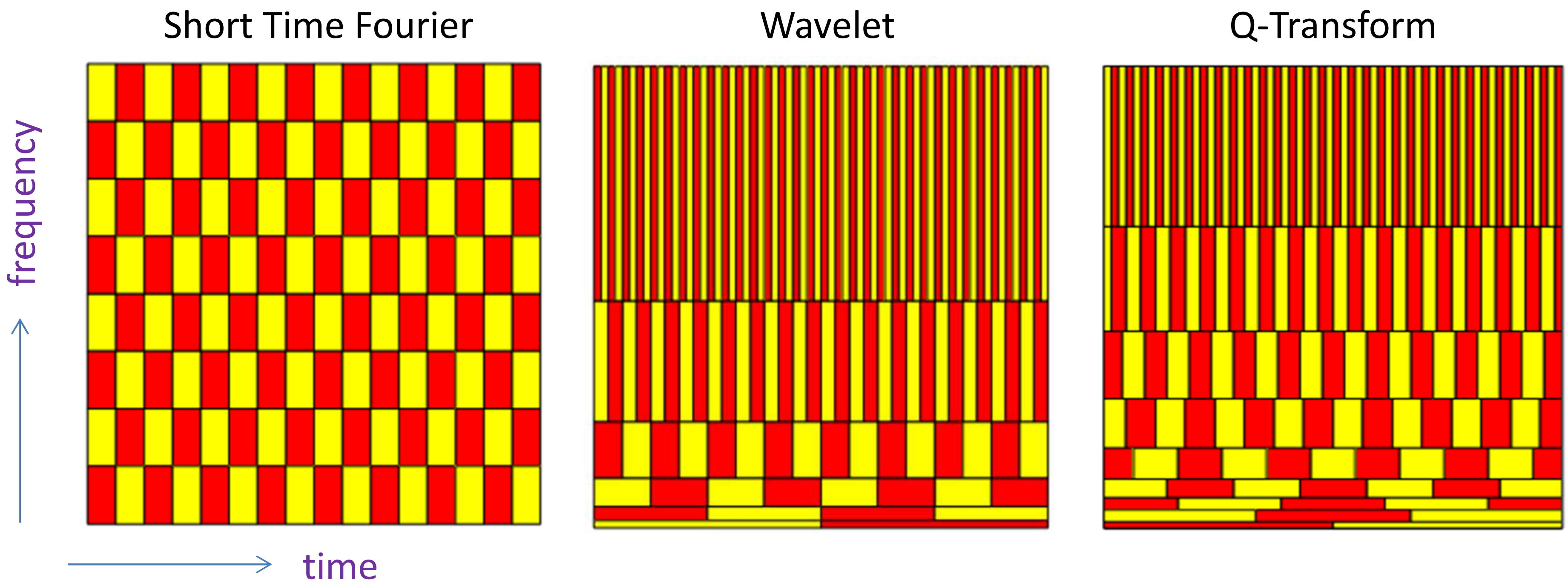
Time frequency distributions suggest an *operational, intrinsic definition* of a *N*-component signal as a signal whose *effective* TF support consists of N *disjoint compact sets*.

$$\boxed{\frac{\boldsymbol{s_1 + s_2}}{\boldsymbol{d_{12}}} < \mathbf{1}}$$



Note : by *effective* TF support here, we mean (following Bedrosian) the TF region where the signal energy exceeds the floor level due to measurement noise or representation accuracy.

Linear TF representations



QT became a std tool in GW data analysis (*Qscan, Omega and Omicron LIGO-Virgo pipelines*). QT can be regarded as template bank (in the whitened signal manifold), consisting of sine-Gaussians with different center time t_0, center frequency f_0, and quality factors Q. Typically, $Q \in (4, 64)$ and $f_0 \in (10^2, 10^3)$ Hz.

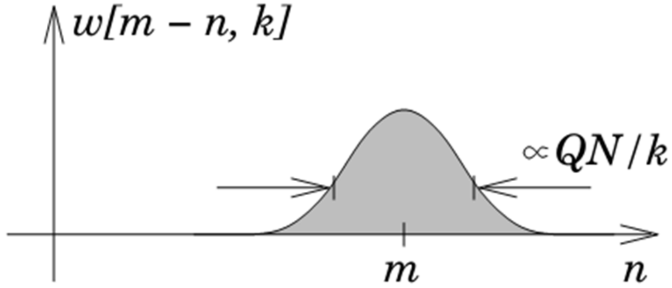
The Q-Transform

Project signal into time-shifted, time-windowed-sinusoids , whose time-widths are *inversely proportional* to their center frequencies.

frequency

$$X_Q[m,k] = \sum_{n=0}^{N-1} x[n] e^{-i2\pi nk/N} w[m-n,k]$$

time



Efficient computation in terms of D(W)FT,

$$\tilde{X}[l] = \sum_{n=0}^{N-1} x[n] e^{-i2\pi nl/N}, \quad \tilde{W}[l] = \sum_{n=0}^{N-1} w[n,k] e^{-i2\pi nl/N}$$

$$\longrightarrow \quad X_Q[m,k] = \sum_{l=0}^{N-1} \tilde{X}[l+k] \tilde{W}[l,k] e^{-i2\pi ml/N}$$

[J.C. Brown, JASA 89 (1991) 425 , J. C. Brown and M. S. Puckette, JASA 92 (1992) 2698.]

[S. Chatterji et al., Class. Quantum Grav. 21 (2004) S1809]

Wigner-Ville Transform

Features the *uniformly highest TF localization* among all unitary (energy-preserving, aka Cohen-class) transforms

$$W_x(t,f) = \int_{-\infty}^{+\infty} \tilde{x}\left(t+\frac{\tau}{2}\right)\tilde{x}^*\left(t-\frac{\tau}{2}\right)e^{-i2\pi f\tau}d\tau\,,$$ where: $$\tilde{x}(t) = x(t) + i\,\mathscr{H}[x(t)]$$

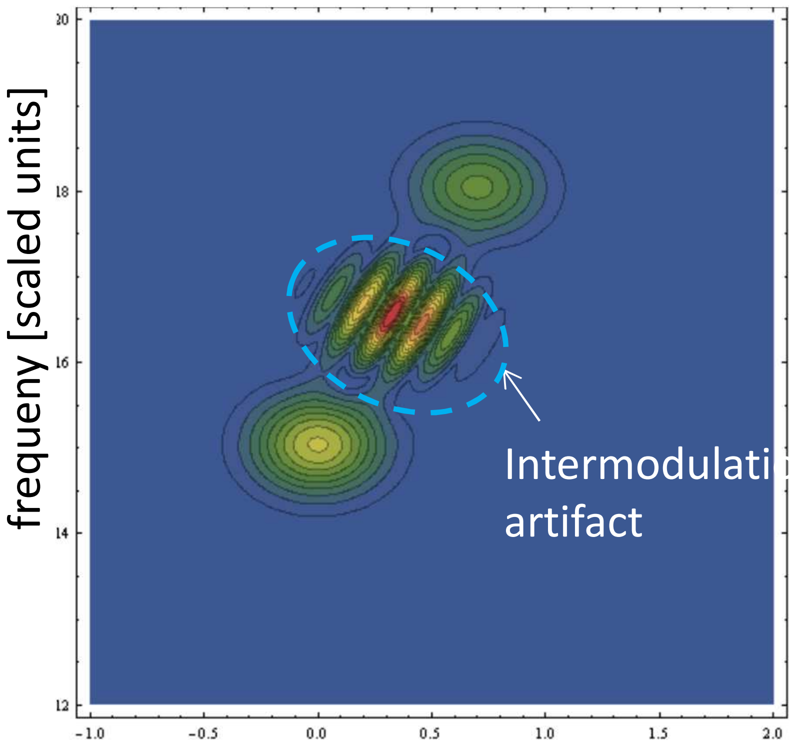
analytic mate of ***x(t)*** **Hilbert transform**

In view of its bilinear nature, the WVT is plagued by *intermodulation artifacts*, except for two very special cases:

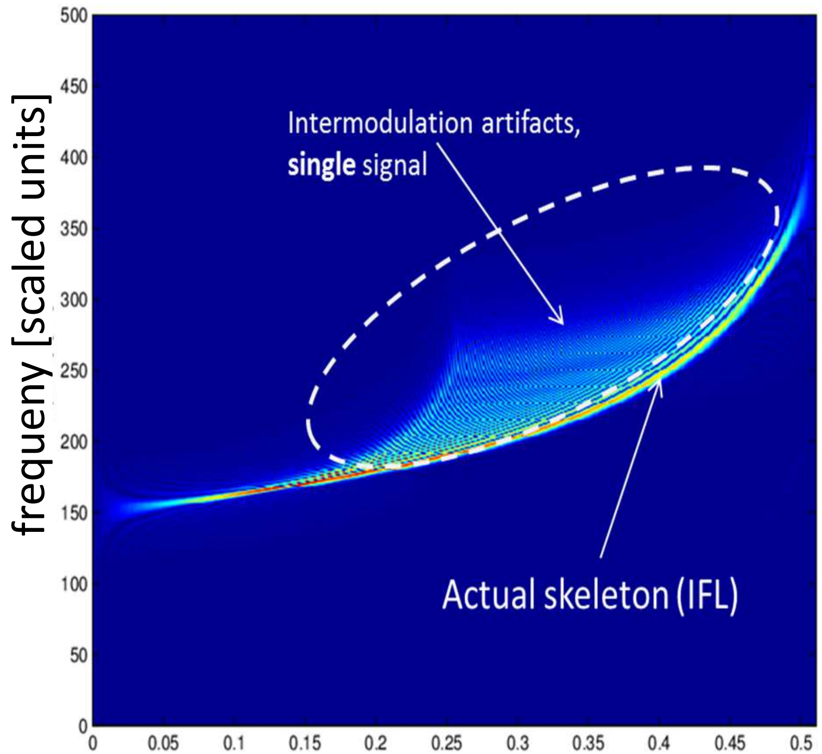
- *linear chirps,* $f = f_0 + \beta t$;
- Gabor (SG) atoms : $s(t) = C\,exp\left[\left(\frac{t-t_0}{\delta t}\right)^2\right]cos[\Omega(t-t_0)]$

WVT Artifacts

WVT of 2-atom Gabor molecule



WV of 0-PN Chirp, $f = f(0)(1 - \frac{t}{t_c})^{-3/8}$



Getting Rid of WVT Artifacts

Smoothing by use of an ambiguity-function (AF) adapted kernel [R. Baraniuk and D. Jones, Signal Proc. 32 (1993) 263] - Husimi / Choi-Williams can be seen as special cases; **Suppress intermodulation terms (which map far from the origin in the AF plane)** ***at the expense of a worse TF resolution***

Re-assigment (re-squeezing) [P. Flandrin et al., IEEE T-SP 43 (1995) 1968] **re-allocate value of smoothed WV at each TF point P to *barycenter* of the WV smoothed by kernel at P**

➡ Retrieving the TF skeleton of the WV from a *reduced cardinality* AF-data subset, using a ***sparsity constraint*** [P. Flandrin and P. Borgnat, IEEE T-SP58 (2010) 2974 ; P. Addesso et al., LIGO-P1200170]

TF Skeleton from WVT

Compute Wigner-Ville TF-representation of data *W(t,f)* ;

Compute related ambiguity function (2D Fourier transform of WV) , call it *A(t,f)* ;

Construct Beraniuk-Jones optimal smoothing kernel for *A(t,f)* ;

Identify Beraniuk-Jones optimal smoothing kernel level curves;

Select the contour encircling $\sim N$ samples (*Heisenberg cardinality constraint*);

Find the TF skeleton $\Sigma(\mathrm{t}, \mathrm{f})$ by solving the constrained optimiz-ation problem (sparse synthesis problem)

$$\min_{\Sigma} \|\Sigma\|_0 \text{ subject to } \|\mathfrak{F}(\Sigma) - A\|_2 \leq \varepsilon$$

Tuning: N and ε key params

[P. Addesso et al., LIGO-P1200170; expanded version subm. to PRD (2015)]

Atomic Decomposition

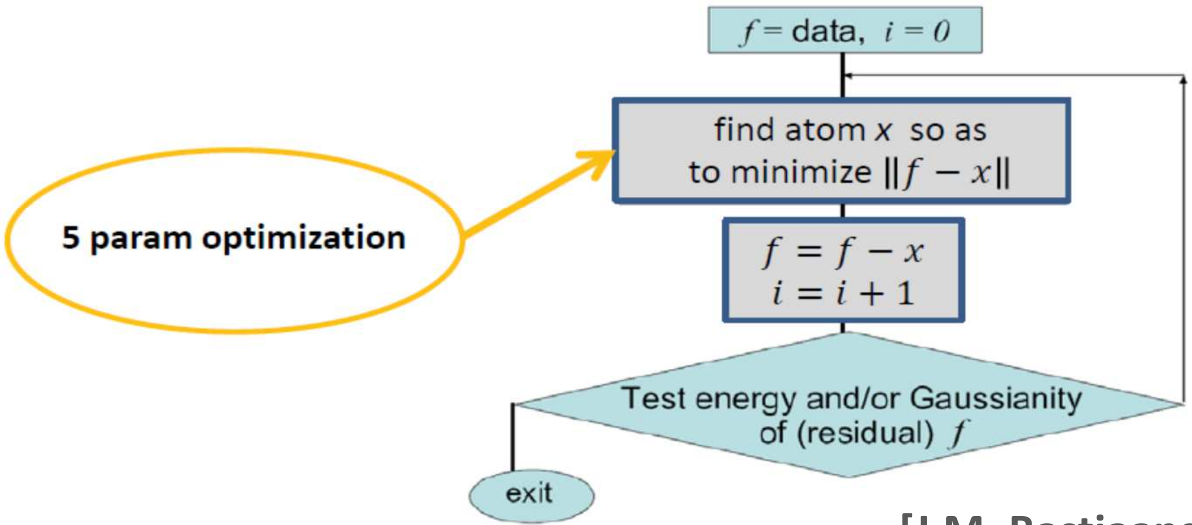
Attempts to decompose a signal into TF "blobs" (TF atoms)

Simplest choice: Gabor (sine-Gaussian) atoms

$$x(t \mid A_0, t_0, f_0, \tau_0, \psi_0) = A_0 exp\left(-\frac{(t-t_0)}{{\tau_0}^2}\right) Cos(2\pi f_0 t + \psi_0)$$

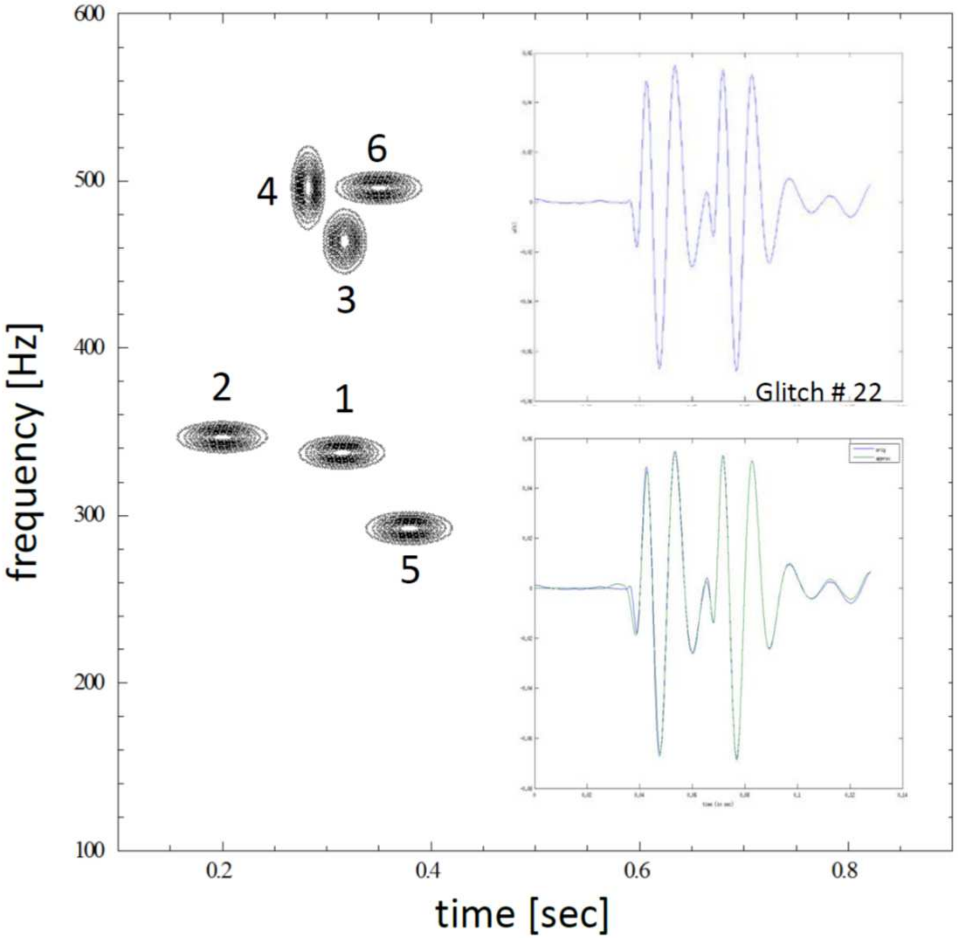
(5 free parameters)

Matching Pursuit (MP) approximation (*greedy* algorithm)



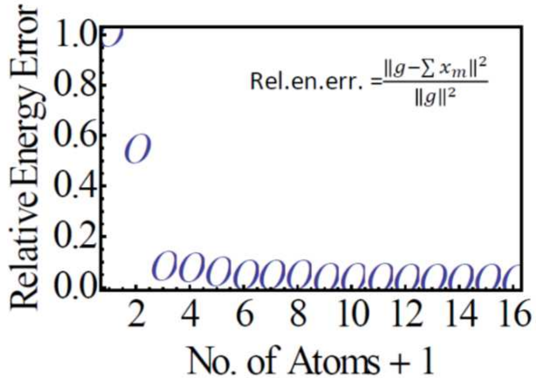
[J.M. Bastiaans, Proc. IEEE 68 (1980) 538]

Atomic Decomposition, contd.



m	A_m	t_m	f_m	τ_m	ψ_m	err_{m-1}
1	0.339411	314.525	337.51	36.9824	-0.778158	1.
2	0.339664	199.664	346.794	38.7676	-0.688176	0.536083
3	0.033311	317.117	463.991	18.3848	-0.008061	0.071473
4	0.059282	282.063	495.989	14.1777	-2.50435	0.067004
5	0.055749	378.865	292.419	37.0195	1.49288	0.052851
6	0.010988	349.75	495.989	37.2266	2.08993	0.040335
7	0.031284	225.506	201.535	72.75	-1.54849	0.039849
8	0.052121	236.	495.989	44.0488	-3.75086	0.035908
9	0.010925	286.563	495.989	-7.29688	-1.49696	0.024968
10	0.004872	304.848	319.056	77.9707	-0.390494	0.024487
11	0.029298	507.117	286.594	62.916	7.90958	0.024391
12	0.006489	443.998	463.971	91.6738	5.85081	0.020935
13	0.002232	329.318	208.774	3.45313	-0.084683	0.020765
14	0.001885	336.752	310.541	-4.35156	0.628395	0.020745
15	0.007372	275.125	467.546	4.39648	-2.59703	0.020731
16	0.061547	162.752	463.991	20.0586	-6.72294	0.020512

t_m, τ_m [ms]

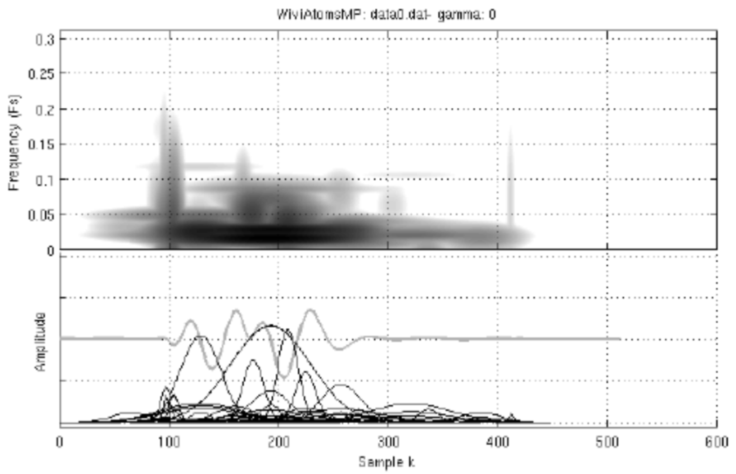


[A. Fusco, work in progress, 2014]

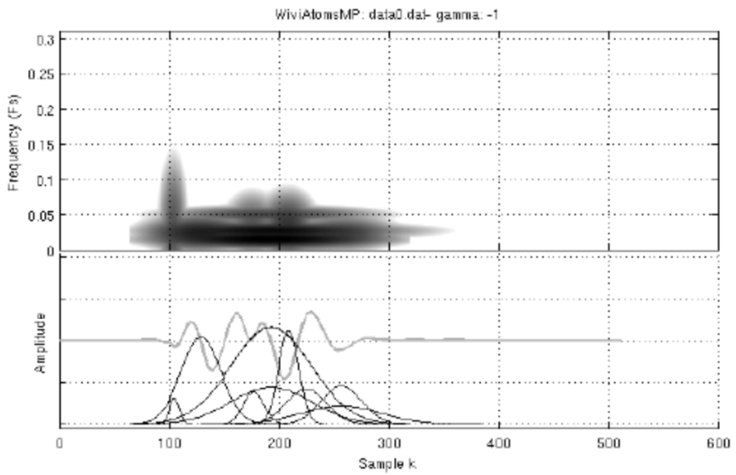
AD Dark Energy Problem

Naïve atomic decomposition shows atoms which are strikingly outside the time support of the glitch (dark-energy atoms) . Must include a penalty functional in the greedy optimization algorithm

naive



smart



Hilbert-Huang Transform

Step 1 - "decompose" signal into Huang's ***intrinsic modes***

$$s(t) = \sum_{k=1}^{N} a_k(t) cos[\phi_k(t)]$$

No sound theoretical basis.
Just an algorithm ("sifting").
NASA hold several related patents.

signal has at least one max & one min (otherwise must be differentiated first);

"time scale" defined by time lapse between extrema;

at any point, mean value of the (local) max-envelope and (local) min-envelope is zero for each IMF;

In each IMF the number of min, max and zero crossings does not differ by more than 1.

[N. Huang, Proc. Roy. Soc. *A554* (1998) 903]

Step 2 - compute Hilbert – transform ($\mathcal{H}$) of Huang modes ⟶ *(sparse) TF coding*

$$A_k(t) exp[i\psi(t)] = a_k(t) cos[\phi_k(t)] + i \mathcal{H}\{ a_k(t) cos[\phi_k(t)] \}$$

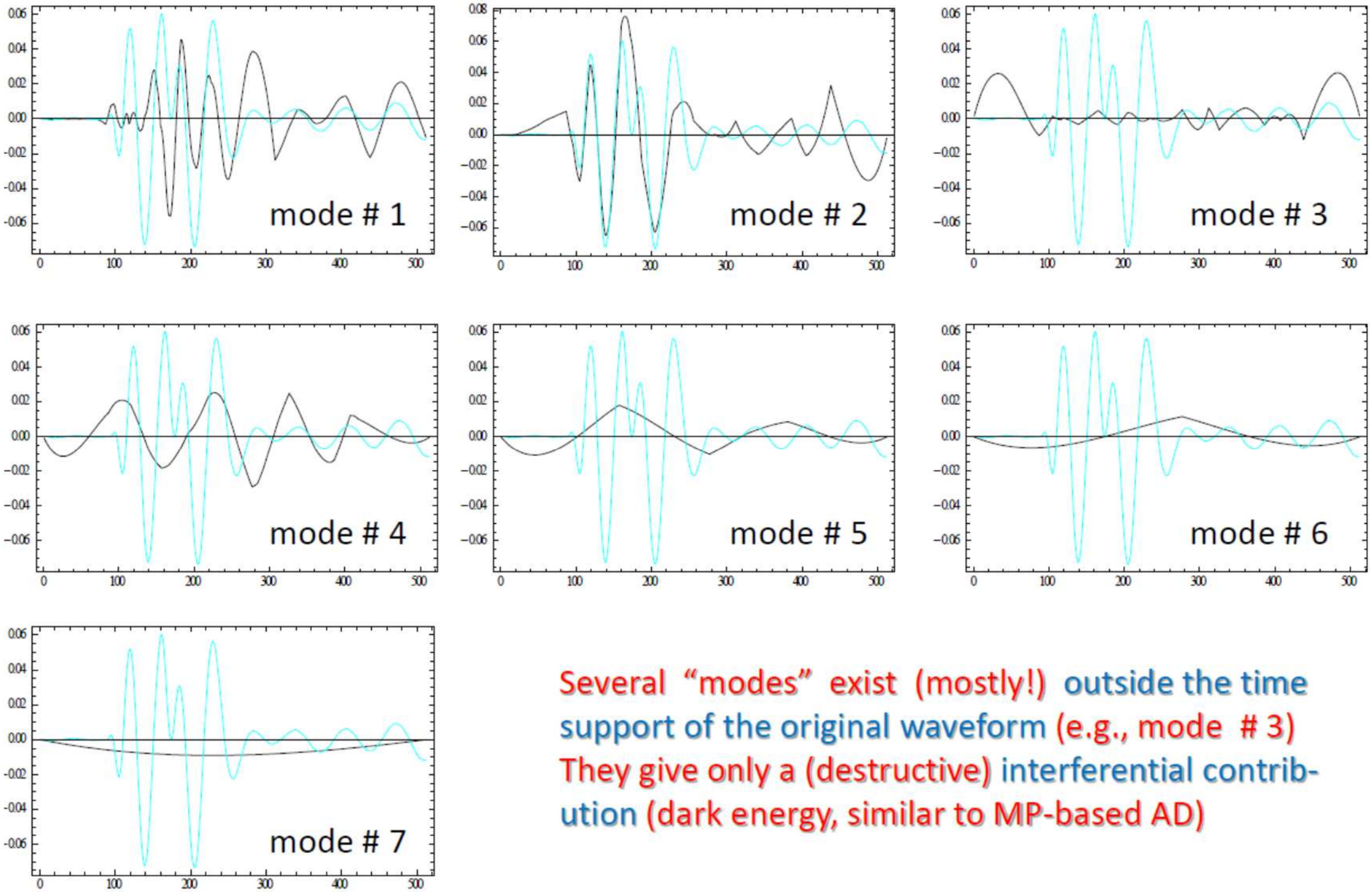
⟶ $\omega_k(t) = \frac{d\psi_k}{dt}$ *(instantaneous frequencies)*

$A_k(t)$ *(instantaneous amplitudes)*

Step 3 - **Encode signal into a set of *ridges (1D-TF features)* :** $HHT[s] = \sum_{k=1}^{N} A_k(t) \delta[\omega - \omega_k(t)]$

Dark Energy in EMD

Huang empirical modes (original waveform in cyan)



Several "modes" exist (mostly!) outside the time support of the original waveform (e.g., mode # 3)
They give only a (destructive) interferential contribution (dark energy, similar to MP-based AD)

Other HHT Issues

i) The IMF decomposition is not unique: there is an infinite number of IMF choices which will reproduce the same s(t), differing in the way the non-stationarity is embedded in the AM, FM or both.

ii) The claim frequently made in the GW Literature that "the HH method achieves *infinite frequency resolution*" is unsubstantial

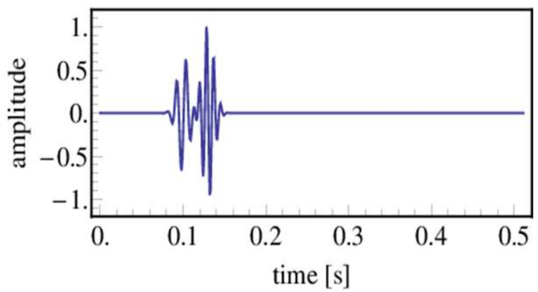
[P. Flandrin, IEEE T-SP IEEE Trans. Signal Proc. 56 (2008) 85]

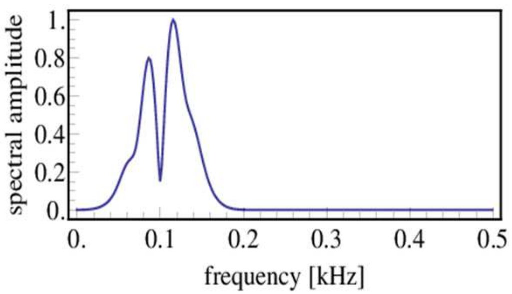
iii) The numerical differentiation used to retrieve the instantaneous frequency is quite sensitive to noise. Boashash and coworkers compared the STFT, WD, RGK-smoothed WV, BD, HHT in the presence of noise for a number of representative waveforms. They found that the RGK-smoothed WV and the HHT gave the best and worst performance, respectively.

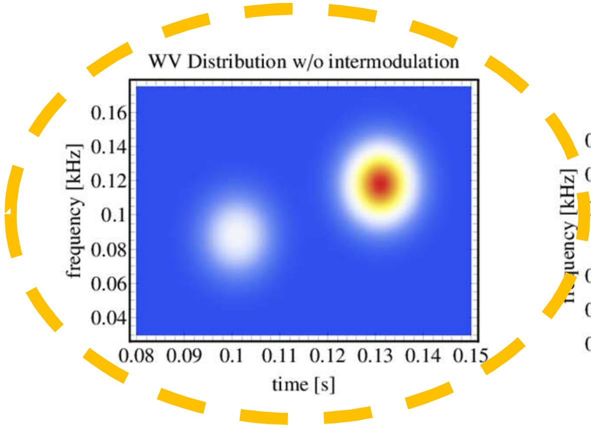
[N. Stevenson et al., IET Signal Proc. 4 (2010) 447]

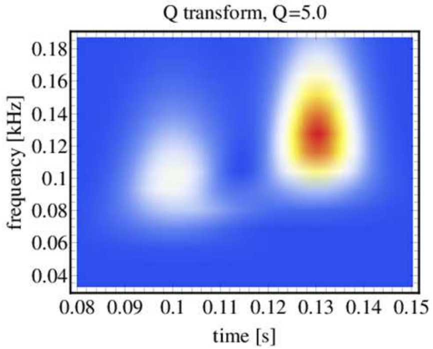
QT vs WVT vs CS-WVT vs HHT

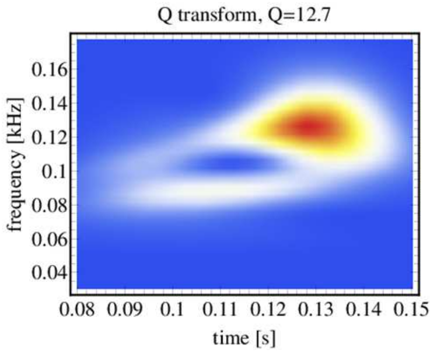
Gabor Molecule

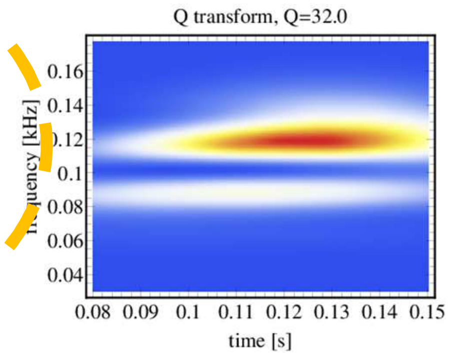


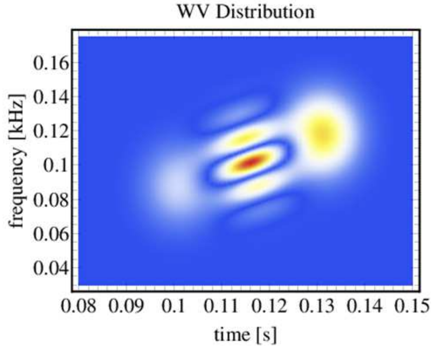


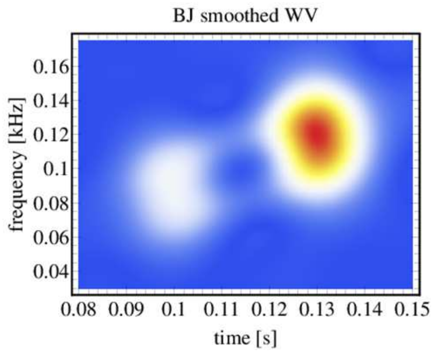


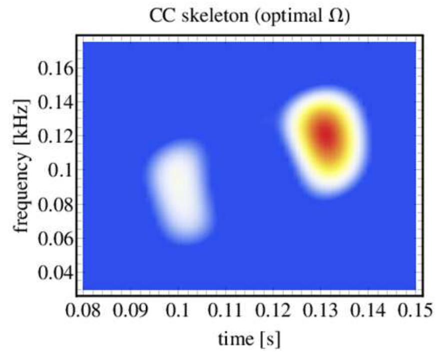


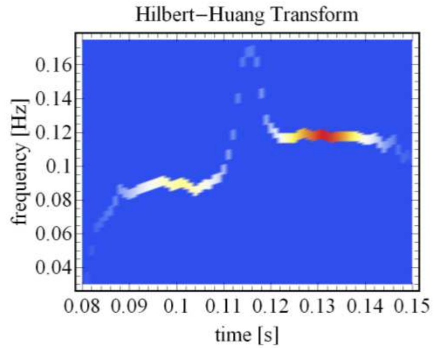


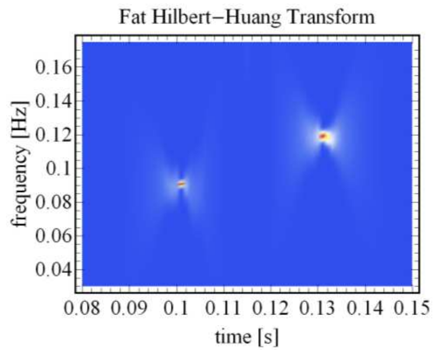






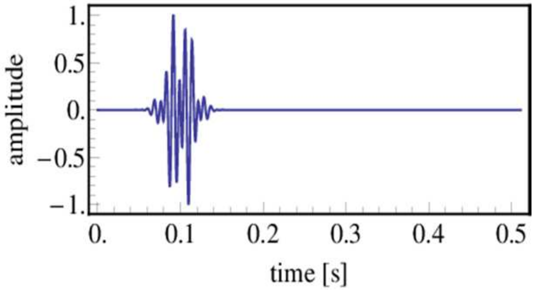


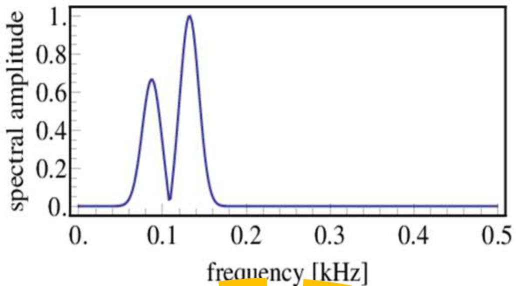


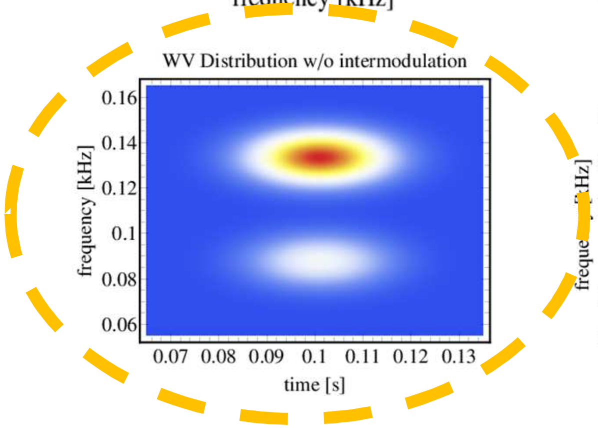


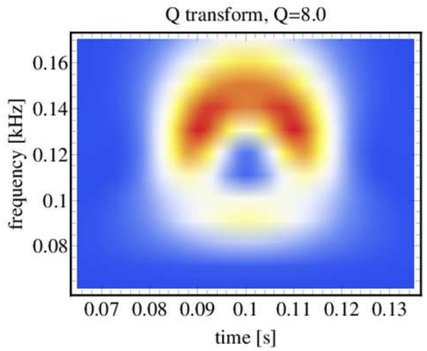
QT vs WVT vs CS-WVT vs HHT, contd.

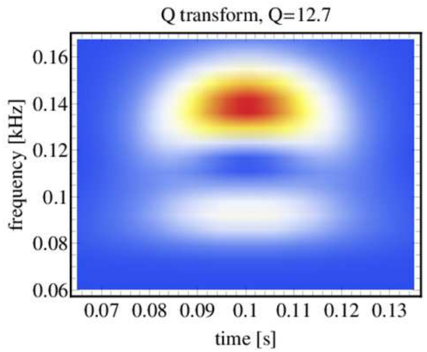
Gabor Molecule (beat)

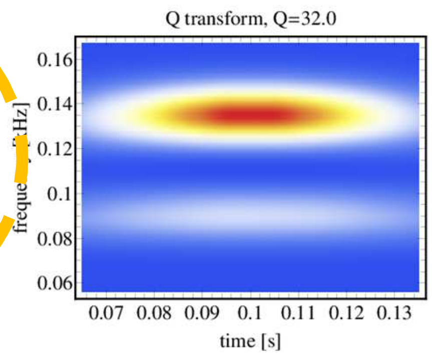


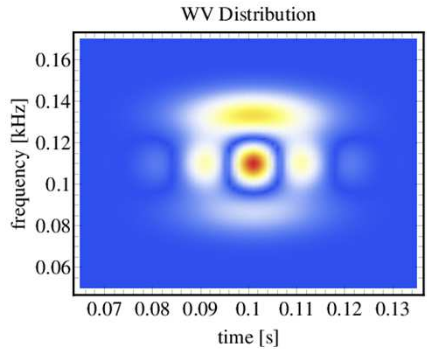


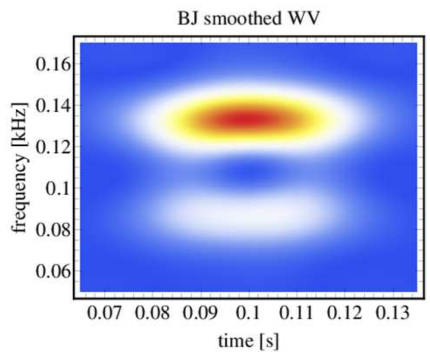


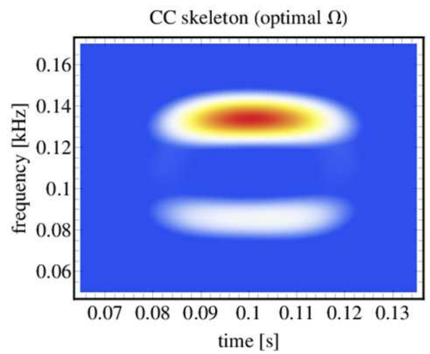


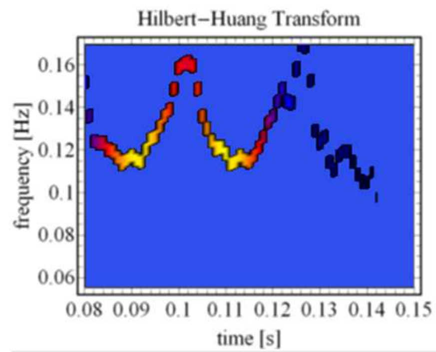


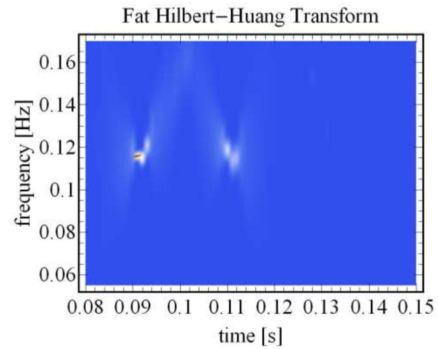






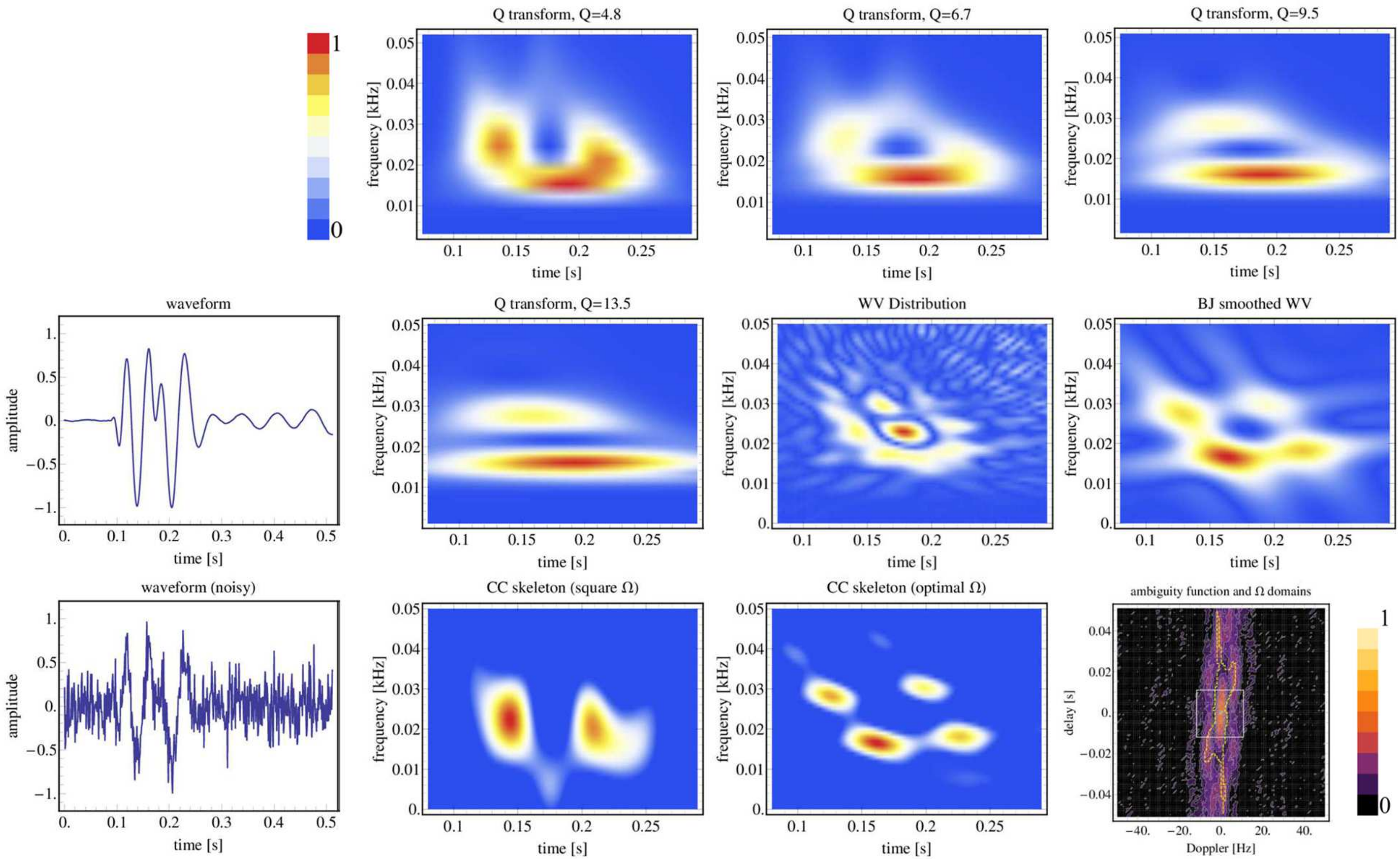






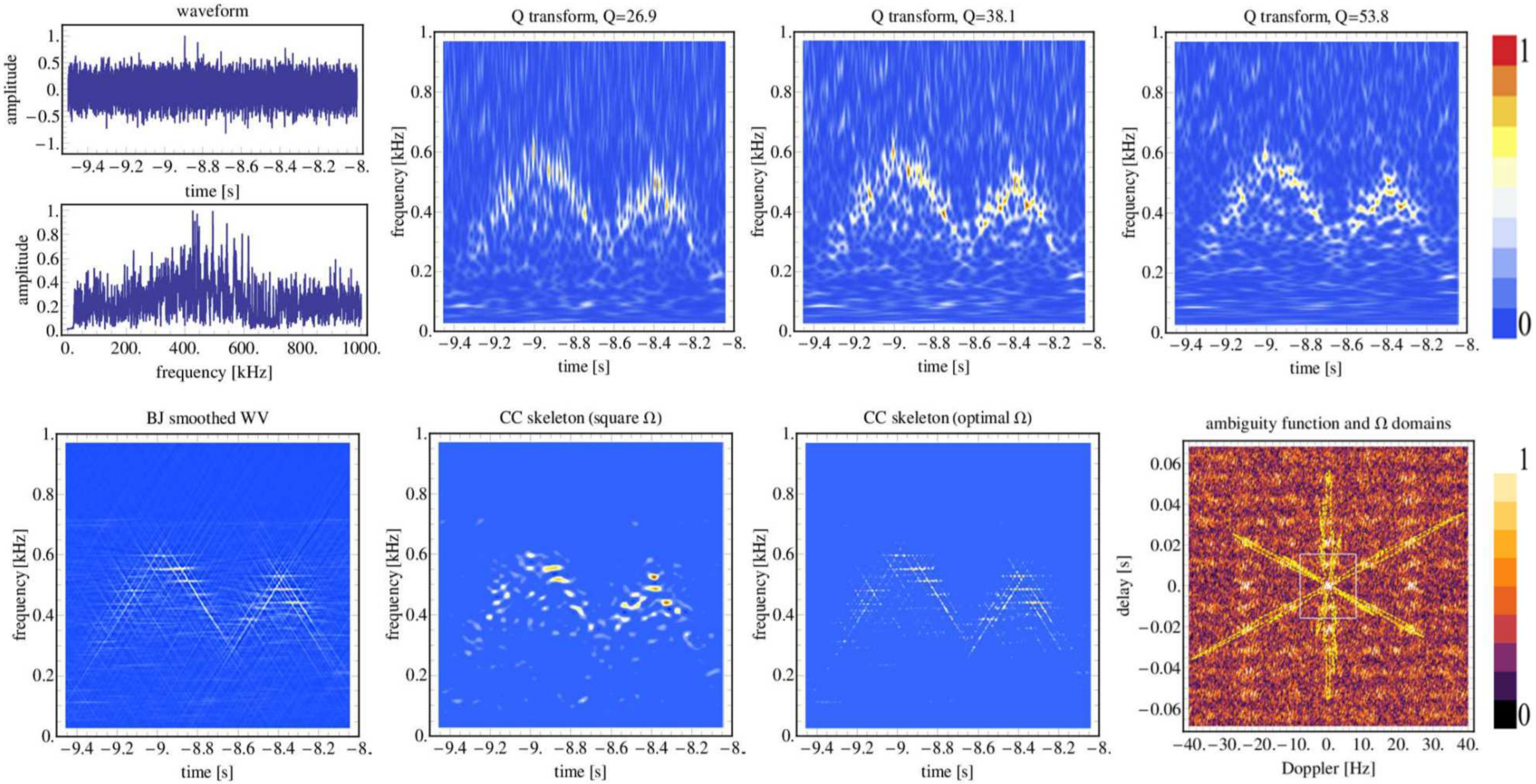
HHT is fooled by the beat !!

A Multi Component Glitch (LIGO, S5)



more in [V. Pierro et al., Ligo-T1300598]

A Nonlinear (GEO 600) Glitch



Outlook

Glitch Busting

➡ Assembling Glitch Databases

Glitch Enthomology

Glitchy Noise Modeling

A Simple, Physically Driven Model

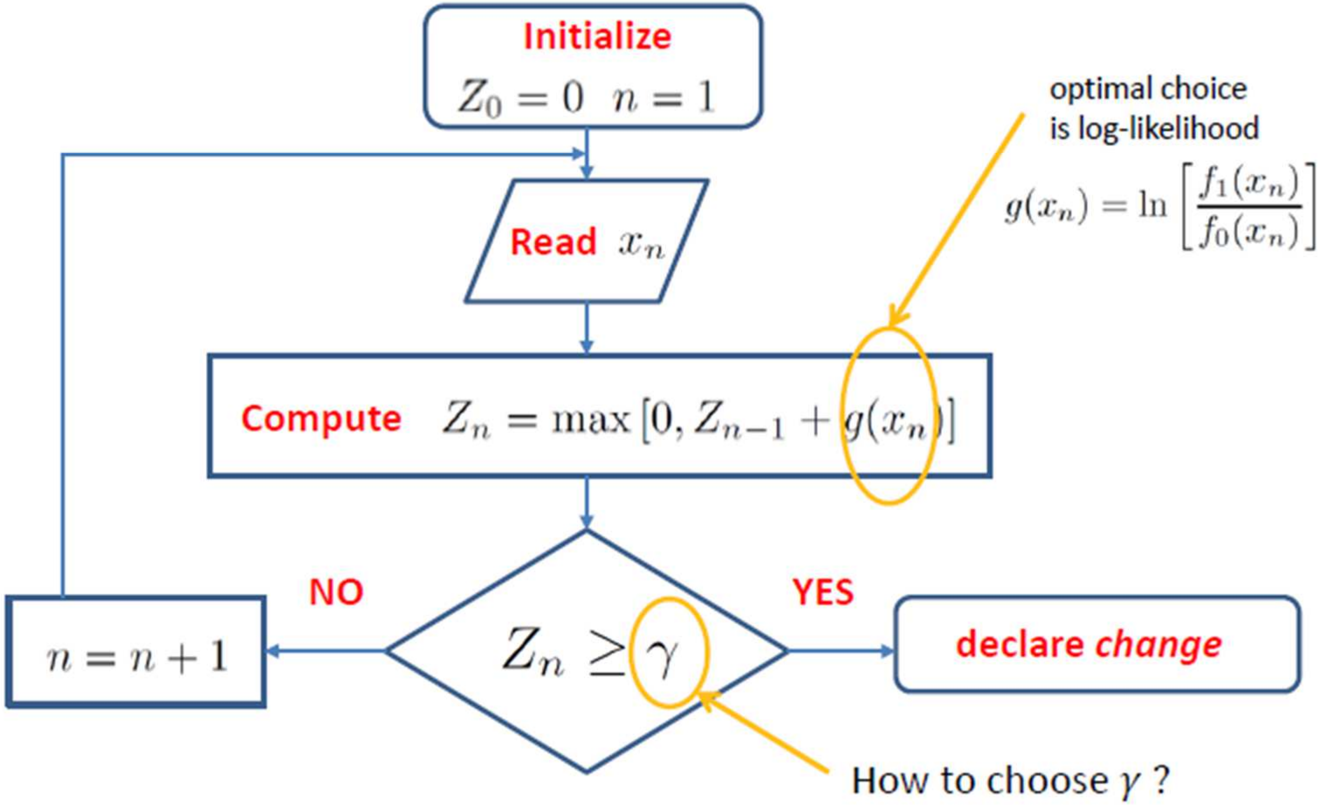
Proto Glitches, PCA, and Beyond

Ongoing Work

Page Test for Glitch Detection

Original formulation **(CUSUM change detection test)**

Let $\{x_n | n = 1,2,\ldots,N\}$ a time series; x_n has density $\begin{cases} f_0(x_n), & n \le n_0 \\ f_1(x_n), & n > n_0 \end{cases}$



Page Test - from N(0,σ_0) to N(0, σ_1)

$$f_i(x) = \frac{1}{\sigma_i\sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma_i^2}\right) \quad , i=0,1 \quad \Longrightarrow \quad g(x_n) = \frac{x_n^2}{2}\left(\frac{1}{\sigma_0^2} - \frac{1}{\sigma_1^2}\right) - \ln\left(\frac{\sigma_1}{\sigma_0}\right)$$

Define : $\frac{\sigma_1^2}{\sigma_0^2} = 1 + \rho$, $\quad \Longrightarrow \quad g(x_n) = \frac{1}{2}\left[\left(\frac{\rho}{1+\rho}\right)\frac{x_n^2}{\sigma_0^2} - \ln(1+\rho)\right]$

this is a sort of "contrast " (aka SNR)

Set maximum **false alarm rate**, $T_f^{-1} \Longrightarrow T_f f_s = N_f$ = min. # samples between f.a.

Compute **threshold** : $\gamma = ln\{-N_f E[g(x)|H_0]\} = ln\left\{\frac{N_f}{2}\left[ln(1+\rho) - \frac{\rho}{1+\rho}\right]\right\}$

Detector performance measured in terms of **average delay in change-detection**

$$N_d = \frac{\gamma}{E[g(x)|H_1]} = \frac{2\gamma}{\rho - ln(1+\rho)}$$

... ***transients*** **shorter than this will *not* be detected, on average ...**

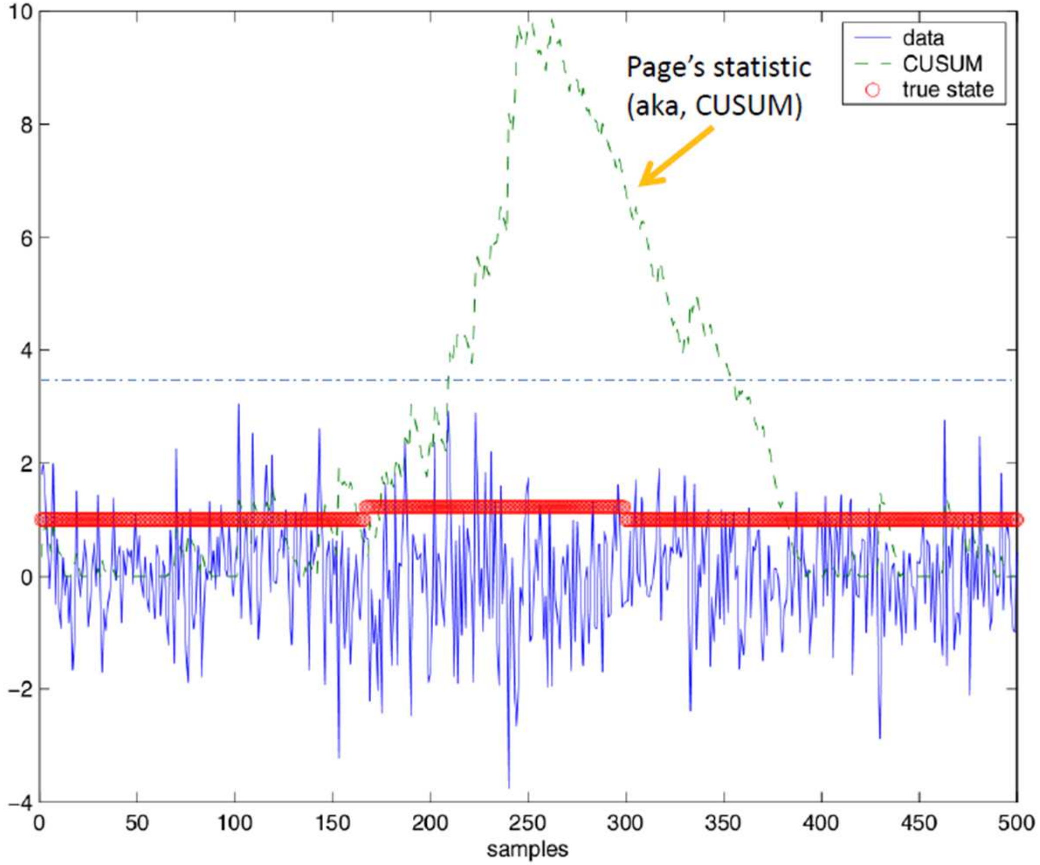
Note: N_f is **exponential** in γ
N_d is **linear** in γ

For fixed γ, length of *shortest* detectable *transient* scales inversely with SNR

$\Longrightarrow N_d(\rho') < N_d(\rho), \forall \rho' > \rho,$

Page Test, contd.

Example: change of variance occurring in finite interval



... see discussion in:

Wang and Willett,
IEEE Trans SP-48 (2000) 2682

Wang and Willett,
IEEE AES Conf Proc 2005
Paper # 1536

Wang and Willett,
IEEE Trans SP-53 (2005) 4397

Easily *robustified* if σ_0 fluctuates :

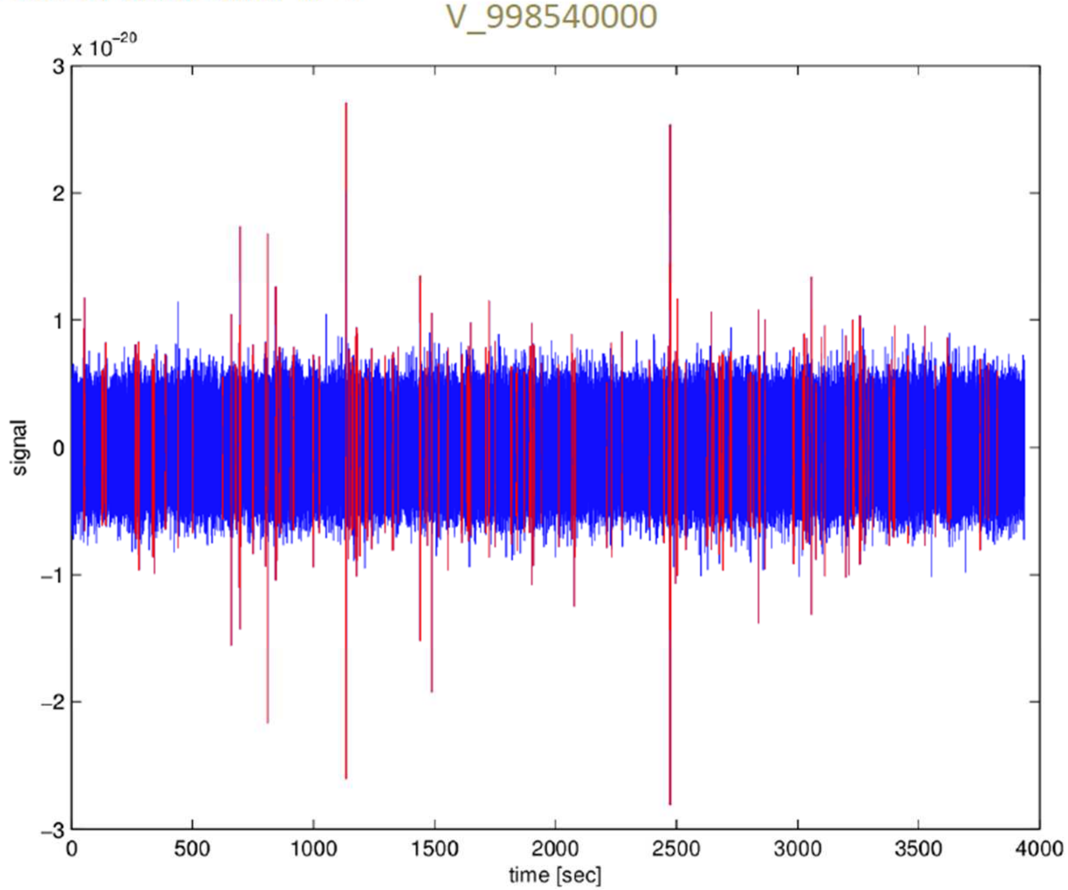
$$\sigma_{0,r} = c\widehat{\sigma}_0 \ , \ c > 1$$

$$\Longrightarrow \quad T_f(\sigma_{0,r}) < T_f(\sigma_{0,r})$$

Collaborations with Peter Willett's group active since long [V. Matta]...

Page Test Sample Output

Fast : 4 sec CPU
to sieve 4000 sec of data on a i7 !



$c=1.2$
$F_{inf}=10$
$F_{sup}=256$
$N_C=4000$ sec
$f_s=4096Hz$
$f'_s=512Hz$

Note: *different* vertical scales, set to accommodate largest glitch in chunk

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➡ A Simple, Physically Driven Model
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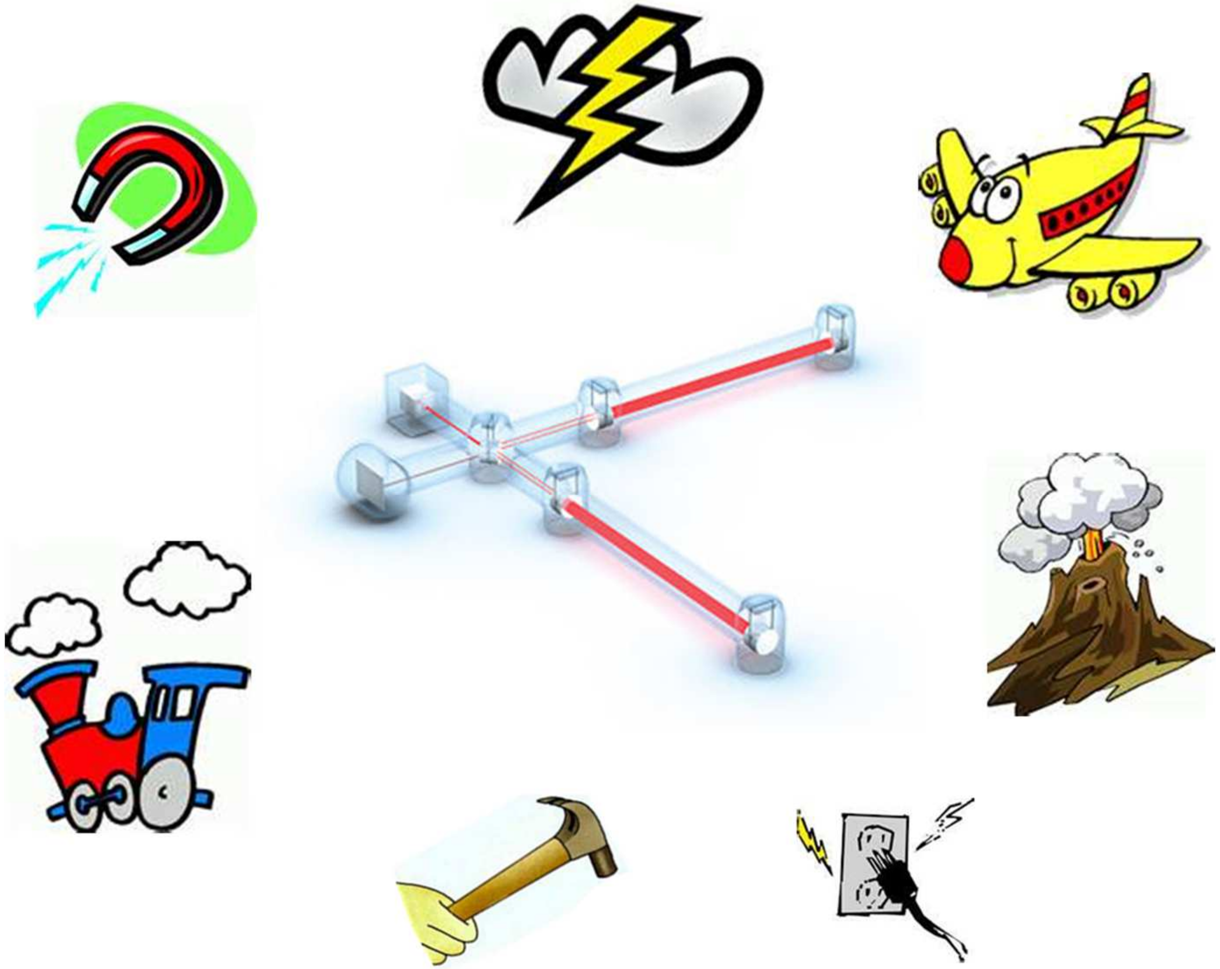
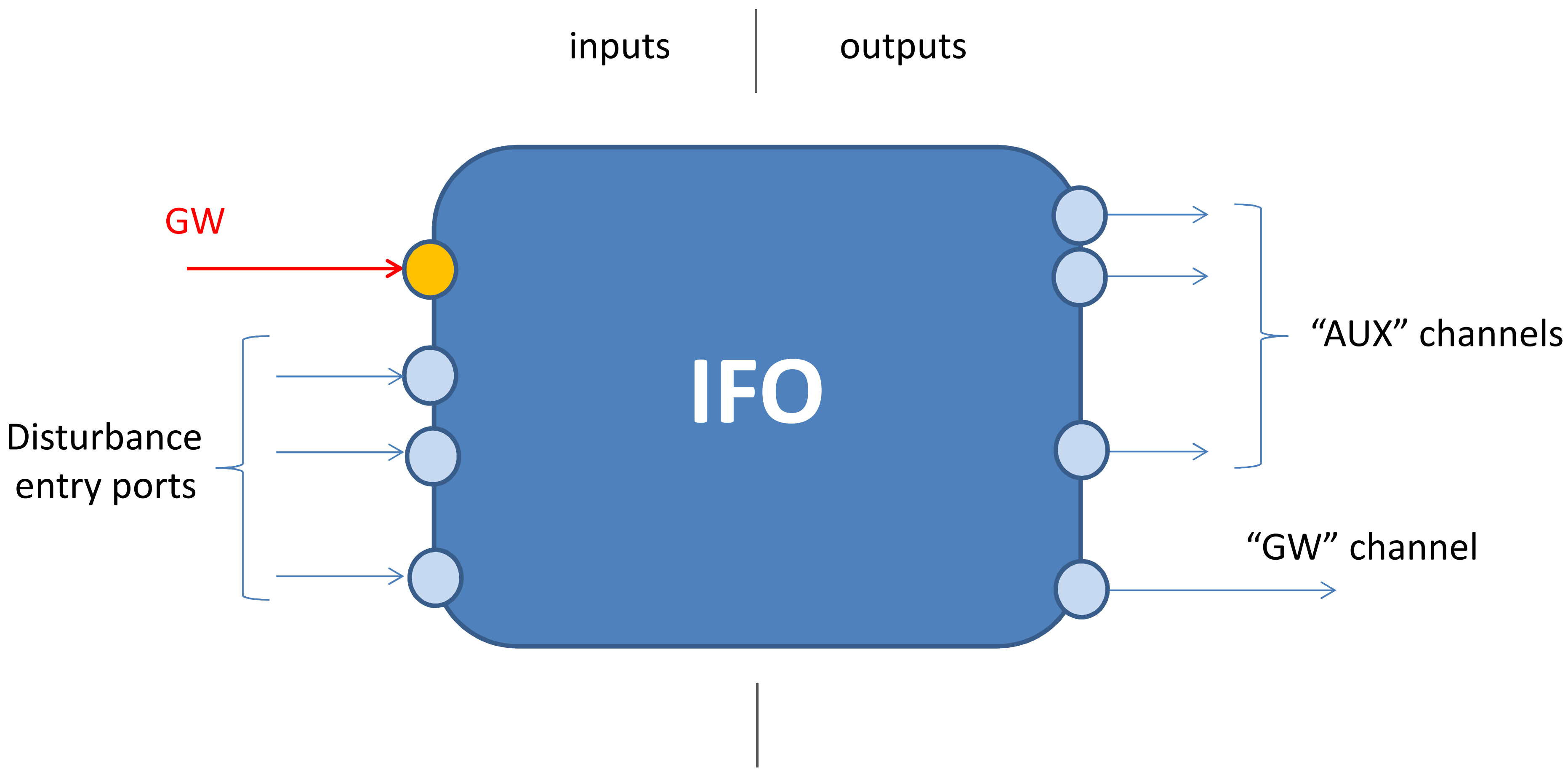
Disturbances



GW Interferometer as MIMO



Linear MIMO I/O Description

In frequency (Fourier) domain:

$$\begin{pmatrix} y_1(\omega) \\ y_2(\omega) \\ \cdots \\ y_N(\omega) \end{pmatrix} = \begin{pmatrix} H_{11}(\omega) & H_{12}(\omega) & \cdots & H_{1M}(\omega) \\ H_{21}(\omega) & H_{22}(\omega) & & H_{2M}(\omega) \\ & \cdots & & \\ H_{N1}(\omega) & H_{N2}(\omega) & \ldots & H_{NM}(\omega) \end{pmatrix} \begin{pmatrix} x_1(\omega) \\ x_2(\omega) \\ \cdots \\ x_M(\omega) \end{pmatrix}$$

$H_{pq}(\omega)$ = transfer function between input-port #q and output-port #p

Nonlinear Input/Output

Volterra-Wiener series [M. Schetzen, *The Volterra and Wiener Theories of Nonlinear Systems,* Krieger, (2006)]

linear response

linear kernel, $h(t) = \mathfrak{F}^{-1}\left[H(\omega)\right]$

nonlinear response (quadratic term)

nonlinear response (cubic term)

$$y(t) = \int_{-\infty}^{\infty} d\tau\, h_1(t;\tau)\, x(\tau) +$$

$$+ \int_{-\infty}^{\infty} d\tau_1 \int_{-\infty}^{\infty} d\tau_2\, \boxed{h_2(t;\tau_1,\tau_2)}\, x(\tau_1)x(\tau_2) +$$

$$+ \int_{-\infty}^{\infty} d\tau_1 \int_{-\infty}^{\infty} d\tau_2 \int_{-\infty}^{\infty} d\tau_3\, \boxed{h_3(t,\tau_1,\tau_2\tau_3)}\, x(\tau_1)x(\tau_2)x(\tau_3) + \ldots$$

nonlinear (quadratic, cubic, etc.) Volterra-Wiener kernels

… straightforward in principle…

Nonlinear Input/Output, contd.

Spectral forms (time-invariant systems)

$$y(t) = \int_{\infty}^{\infty} df\ H_1(\omega)X(\omega)\, exp(\imath\omega t) +$$

2D Fourier transform of $h_2(\cdot)$

$$+ \int_{\infty}^{\infty} df_1 \int_{\infty}^{\infty} df_2\, H_2(\omega_1,\omega_2)X(\omega_1)X(\omega_2)exp[\imath(\omega_1+\omega_2)t] +$$

3D Fourier transform of $h_3(\cdot)$

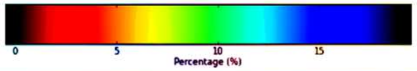
$$+ \int_{\infty}^{\infty} df_1 \int_{\infty}^{\infty} df_2 \int_{\infty}^{\infty} df_3\, H_3(\omega_1,\omega_2,\omega_3)X(\omega_1)X(\omega_2)X(\omega_3)exp[\imath(\omega_1+\omega_2+\omega_3)t] + \cdots$$

Spectral Volterra-Wiener kernels

$\mathfrak{F}$

$$Y(\omega) = \sum_{n=1}^{\infty} Y^{(n)}(\omega) = \int_{\infty}^{\infty} df_1 \int_{\infty}^{\infty} df_2 \ldots \int_{\infty}^{\infty} df_n\, H_n(\omega_1,\ldots,\omega_n) \prod_{p=1}^{n} X(\omega_p)\, \delta\left(\omega - \sum_{q=1}^{n} \omega_q\right)$$

Nonlinear Glitches

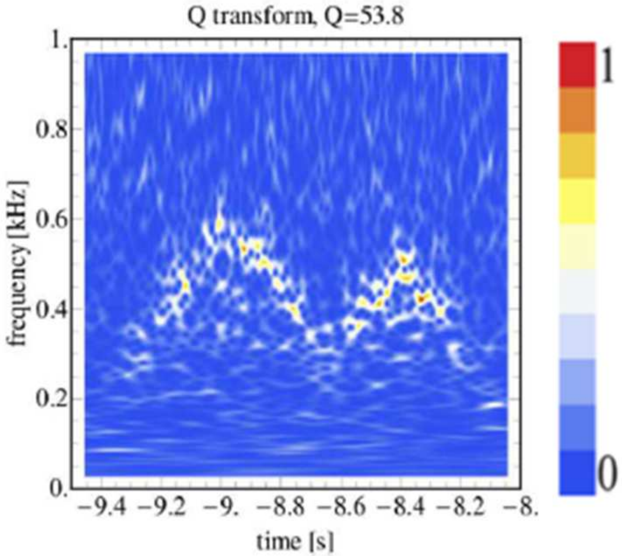


“Fast” channels

“Slow” channels

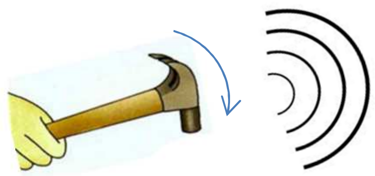
Channel Name	H1:ASC-ETMX_P	H1:ASC-ETMX_Y	H1:ASC-ETMY_P	H1:ASC-ETMY_Y	H1:ASC-ITMX_P	H1:ASC-ITMX_Y	H1:ASC-ITMY_P	H1:ASC-ITMY_Y	H1:LSC-MICH_CTRL	H1:LSC-PRC_CTRL
H1:LINEAR	6.92%	10.10%	6.31%	11.27%	11.33%	10.29%	8.70%	11.08%	11.27%	
H1:ASC-QPDX_P	6.74%	10.10%	6.67%	7.41%	8.57%	7.72%	8.14%	9.06%	13.60%	14.21%
H1:ASC-QPDX_Y	10.23%	10.23%	2.08%	7.17%	8.82%	9.06%	4.04%	6.06%	13.84%	15.19%
H1:ASC-QPDY_P	9.55%	8.94%	3.98%	6.92%	9.74%	8.45%	5.21%	6.80%	12.19%	14.45%
H1:ASC-QPDY_Y	6.80%	5.57%	6.67%	5.94%	7.66%	8.14%	6.00%	7.35%	10.84%	8.82%
H1:ASC-WFS1_QP	5.63%	5.08%	10.04%	6.12%	9.12%	8.51%	9.80%	9.00%	10.65%	12.12%
H1:ASC-WFS1_QY	8.63%	14.21%	10.10%	9.86%	7.96%	8.88%	7.59%	8.21%	5.08%	8.45%
H1:ASC-WFS2_IP	9.25%	8.76%	8.02%	9.68%	9.49%	9.19%	12.25%	10.35%	10.29%	13.41%
H1:ASC-WFS2_IY	6.43%	10.35%	7.72%	9.49%	7.59%	8.02%	8.39%	10.59%	8.08%	10.04%
H1:ASC-WFS2_QP	9.68%	11.70%	10.96%	14.45%	8.70%	10.84%	9.06%	12.19%	14.21%	11.14%
H1:ASC-WFS2_QY	8.08%	9.55%	7.35%	9.43%	9.25%	9.31%	8.70%	10.41%	5.57%	13.84%
H1:ASC-WFS3_IP	12.74%	7.78%	7.35%	9.37%	12.86%	5.08%	7.23%	8.45%	10.65%	15.74%
H1:ASC-WFS3_IY	10.35%	13.35%	8.27%	14.15%	12.92%	13.90%	10.84%	12.98%	11.88%	15.86%
H1:ASC-WFS4_IP	10.96%	9.49%	9.86%	12.55%	12.86%	8.88%	8.33%	10.10%	12.68%	14.82%
H1:ASC-WFS4_IY	10.59%	9.19%	8.39%	11.27%	12.25%	5.14%	9.98%	8.76%	12.62%	13.90%

Bi-linear glitch zoo table (LIGO)



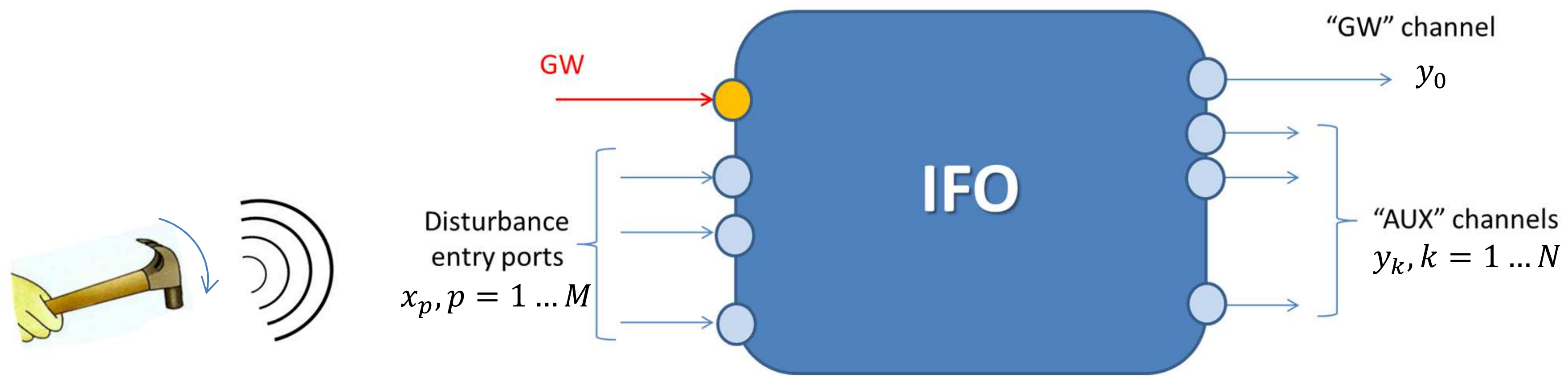
A GEO600 “arch” glitch in TF plot (courtesy M. Was)

Mickey-Mouse (Linear) Model



primary disturbance (spectrum)	disturbance as it reaches IFO entry port # *p*	disturbance as it appears at IFO output port # *k*
$\mathcal{W}(\omega)$	$X_p(\omega) = A_p \mathcal{W}(\omega) \exp(\imath \omega \tau_p)$	$Y_k(\omega) = \sum_{p=1}^{M} H_{kp}(\omega) X_p(\omega)$
you can estimate w PEM	**coupling amplitude and delay, both *essentially random***	

Mickey-Mouse Model, contd.



Disturbance as it appears at IFO output port # *k*

you can estimate from PEM

$$Y_k(\omega) = \sum_{p=1}^{M} H_{kp}(\omega) A_p \mathcal{W}(\omega) \exp(\imath \omega \tau_p)$$

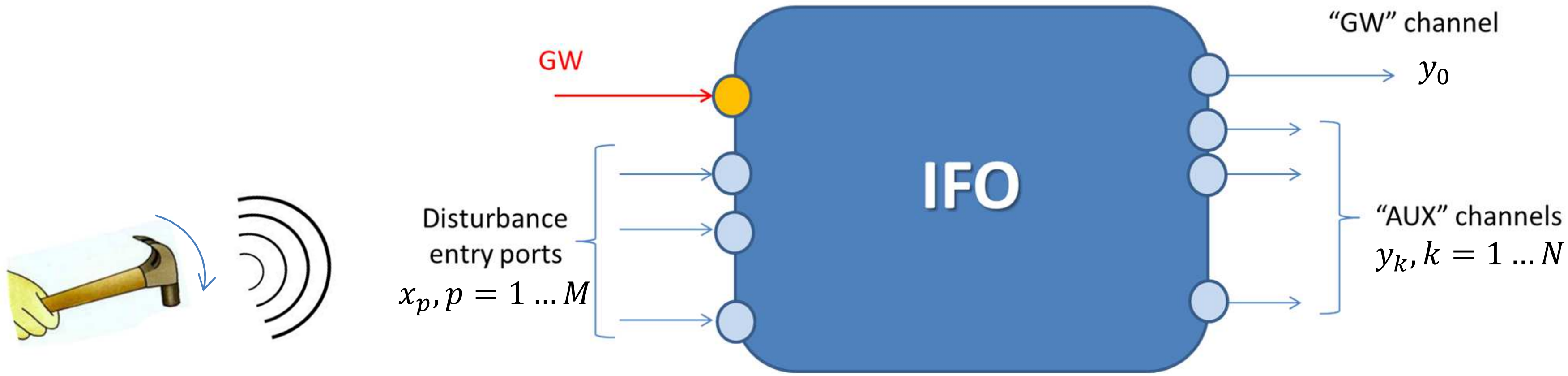
coupling amplitudes and delays are *unknown* *(random)*

Generally, the $H_{kp}(\omega)$ are *not available,* because the IFO disturbance entry-ports are *not accessible* (and may be even *un-identified*)

Simplifying Assumptions

Linearity →	Volterra-Wiener series (some formal complications)
Time-invariance →	wide sense is OK (but update needed)
"Simple" (amplitude/delay) transfer functions from pri-mary disturbance to IFO input ports →	actual transfer functions can be incorporated in the H_{pq}
Many disturbances →	straightforward

Wideband (Short) Disturbances



Disturbance as it appears at IFO output port # *k*

$$Y_k(\omega) = \sum_{p=1}^{M} H_{kp}(\omega) A_p \exp(\imath\omega\tau_p) \Longleftrightarrow y_k(t) = \sum_{p=1}^{M} A_p h_{kp}(t - \tau_p)$$

➡ **Disturbances appear at IFO output ports as linear combinations (with random amplitudes and delays) of a *finite* (M) number of (wide sense) *invariant* waveforms, the $h_{kp}(t)$.**

Wideband (Short) Glitches

All short glitches in the GW data channel are linear superpositions of *the same M* functions

$$y_0(t) = \sum_{p=1}^{M} A_p h_{0p}(t - \tau_p) \iff Y_0(\omega) = \sum_{p=1}^{M} H_{0p}(\omega) A_p \exp(\imath\omega\tau_p)$$

only $\{A_p, \tau_p | \mathrm{p} = 1 \ldots M\}$ (amplitudes and delays) are *different* for each glitch.

If $\{h_{op}(t) \,|\, p = 1 \ldots M\}$ *and/or* $\{H_{op}(\omega) \,|\, p = 1 \ldots M\}$ *were known, we could easily* ***reconstruct****, and then* ***cancel by subtraction*** *any/all glitches occurring in the GW data channel.*

We call $\{h_{op}(t) \,|\, p = 1 \ldots M\}$ the ***proto*** *(aka, basic)* ***glitches.***

Glitchy GW Data

- focus on glitchy GW channel (y_0) data;

- GW data containing (only) short glitches can be written

$$Y_0(\omega) = \sum_{p=1}^{M} H_{0p}(\omega) \underbrace{\sum_{g} A_{pg} \exp(\iota\omega\tau_{pg})}_{\text{sum over glitches}} = \sum_{p=1}^{M} \tilde{\gamma}_p H_{0p}(\omega)$$

- *Many* independent glitchy data (realizations) are available containing putatively (provided the instrument is stationary during their collection time) *the same* $h_{0p}(t)$

$$Y_0{}^{(i)}(\omega) = \sum_{p=1}^{M} \tilde{\gamma}_p{}^{(i)} H_{0p}(\omega), \qquad i = 1,2,\dots,Q, \qquad Q \gg M$$

Glitchy GW Data, contd.

- *Many* (independent) glitchy data (realizations) available

$$Y_0^{(i)}(\omega) = \sum_{p=1}^{M} \tilde{\gamma}_p^{(i)} H_{0p}(\omega), \qquad i = 1,2,\dots,Q, \qquad Q \gg M$$

known, measured

unknown, *sought*

unknown *a priori*

unknown (different i correspond to different realization of the random array $\{\tilde{\gamma}_1, \tilde{\gamma}_2, \dots, \tilde{\gamma}_M\}$

Questions

- Do the $h_{0p}(t)$ proto-glitches form a kind of *minimum-redundant dictionary* for representing *generic glitches* ?
- *How many* are they/how many do we need ?
- *How to extract* the $\{\mathrm{H}_{0p}(\omega) \mid p = 1 \dots M\}$ from glitchy datasets ?

…Technically, a BSS - like problem…

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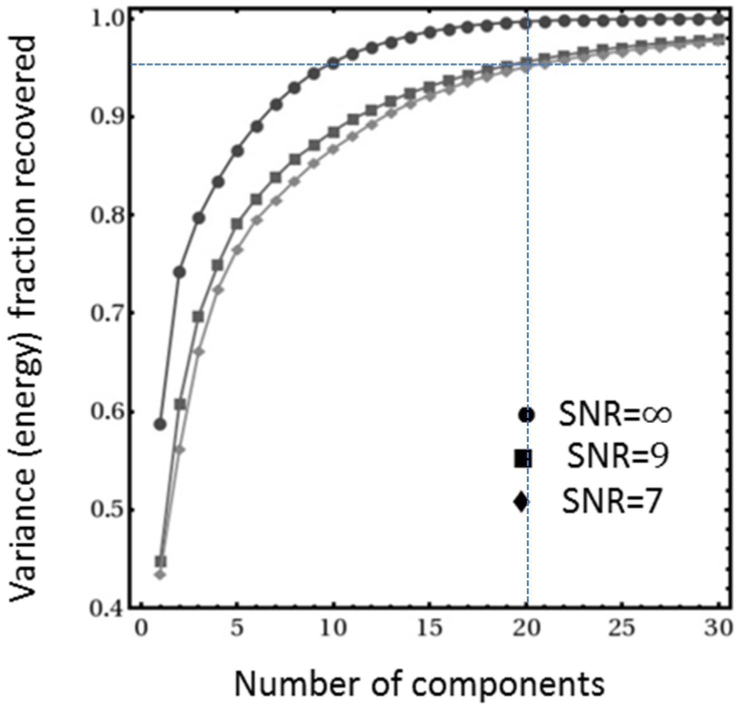
Glitch Enthomology
Glitchy Noise Modeling
A Simple, Physically Driven Model
➡ Proto Glitches, PCA, and Beyond
Ongoing Work

Glitch Manifold Dimensions

Principal Component Analysis (PCA) may answer the question *"how many proto-glitches are there/how many do we need"* .

Specifically, PCA may estimates the dimension of the manifold to which glitches belong.

Independent PCA implementations on different (LIGO) glitch datasets indicate that glitches live in a $\sim \mathbf{20}$ dimensional manifold, to within a $< 5\%$ energy (L^2) error.



[I.M. Pinto, L. Troiano et al., Int. J. Mod. Phys. C24 (2013) 1350084; M. Cavaglia and D. Trifiro', LIGO Document G1300368-v1]

PCA in a Nutshell

Glitches are transient waveforms with time - limited support T, sampled at some frequency f_s. A glitch g is thus represented by *a point* $\boldsymbol{g}$ in Euclidean space R^N, $N = f_s T$.

Let $\mathfrak{D}_{\mathbf{g}} = \{\boldsymbol{g}_i | i = 1,2, \dots, G\}$ our glitch dataset.
Let $\boldsymbol{D}_g$ the N x G matrix whose columns are the $\boldsymbol{g}_i$ vectors ;

1) "Standardize" matrix $\boldsymbol{D}_g$, subtracting from each column its average:

$$\tilde{g}_{ij} = g_{ij} - (1/G) \sum_j g_{ij}$$

2) Compute covariance matrix $\boldsymbol{\Sigma}$ among standardized column vectors :

$$\Sigma_{hk} = (\tilde{\boldsymbol{g}}_h, \tilde{\boldsymbol{g}}_k)$$

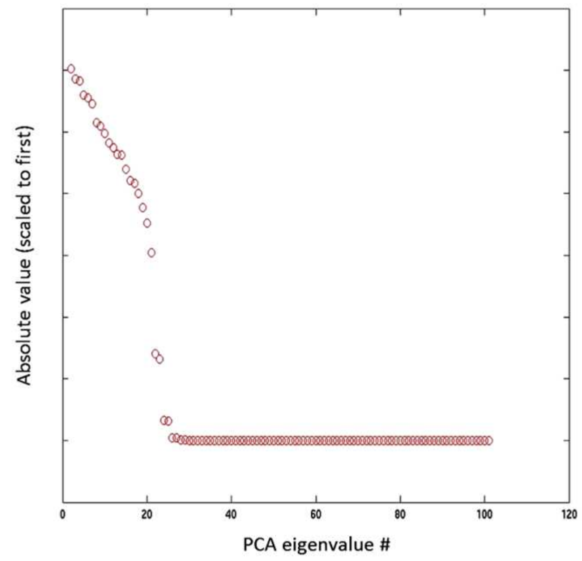
3) Diagonalize $\boldsymbol{\Sigma}$, and enumerate the eigenvalues in order of decreasing (absolute) value. *The corresponding ordered eigenvectors yield the PCA basis* $\{\boldsymbol{\pi}_i | i = 1,2, \dots, G\}$.

[I. T Jolliffe, "Principal Component Analysis," Springer, 2002**]**

PCA in a Nutshell, contd.

The magnitude of the PCA eigenvalues drops steeply beyond a certain order *N**.

Correspondingly, the glitch energy is fully accounted by using only the first *N** vectors from the PCA basis (addition of further terms does *not* improve L^2 accuracy to any sensible extent).



Hence, N* represents a sort of effective dimension of the manifold spanned by the glitch dataset.

PCA appears as a *compressive coding* where the vectors (glitches) $g_i = \{g_{im} | m = 1 \dots N\} \in R^N$, $i = 1 \dots G$, are *encoded* by the vectors $\alpha_h = \{(g_h, \pi_k) | k = 1 \dots N^*\} \in R^{N^*}$, $h = 1 \dots G$, with $N^* < N$.

Glitch Clustering in PC Space

After a glitch dataset $\{\boldsymbol{g_i} | \boldsymbol{i} + \mathbf{1} \ldots \boldsymbol{G}\}$ has been represented in a nonredundant (e.g., PCA) "basis", *clustering algorithms* can be used to identify *families of similar glitches.*

Several glitch clustering algorithms have been proposed/used, based, e.g., on *proximity* ***measures*** in (coarse)-feature space [S. Mukherjee et al., CQG 24 (2007) S701], longest - common-subsequences [S. Mukherjee et al., J. Phys. Conf. Ser. 243 (2010) 012006], Kohonen self-organizing maps [S. Rampone et al., Int. J. Mod. Phys. C24 (2013) 1350085], and ANN [S.M. Kim et al., LIGO-G1201110]

Clustering goodness can be gauged using suitable metrics,e.g., the Davies-Bouldin (DB) index [IEEE T-PAMI, 1 (1979) 224])

Clustering Goodness: DB Index

For each cluster, define a measure of *concentration* (average distance of cluster members from cluster centroid)

$$S_i = \frac{1}{T_i}\sum_{j=1}^{T_i} \|X_j - A_i\|_p \text{ , where } \begin{cases} i = 1 \dots N_c \ (N_c = \text{number of clusters}) \\ A_i = \text{centroid of cluster-}i \\ T_i = \text{number of members in cluster-}i \\ p = 2 \ (\text{Euclidean distance}) \text{ usually} \end{cases}$$

Also, define a measure of *cluster-to-cluster separation*,

$$M_{ij} = \|A_i - A_j\|_p \text{ , where } \begin{cases} i,j = 1 \dots N_c, \ i \neq j \ (N_c = \text{number of clusters}) \\ A_{i,j} = \text{centroid of cluster-}i,j \end{cases}$$

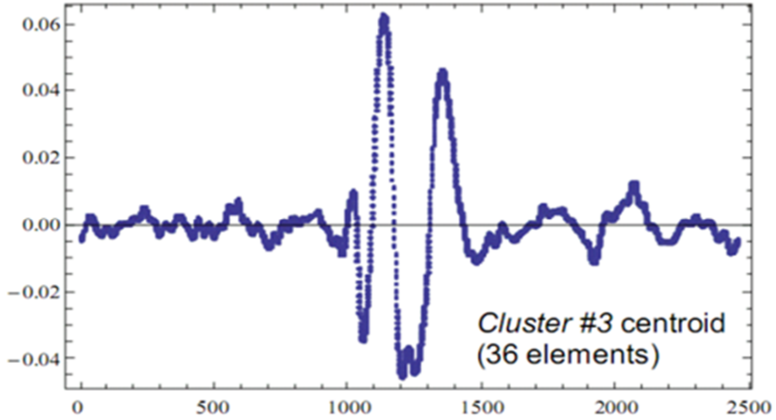
Davies-Bouldin index of clustering goodness is : $\rho_{DB} = \frac{1}{N_c}\sum_{i=1}^{N_c} \max_{j:j\neq i} \frac{S_i + S_j}{M_{ij}}$

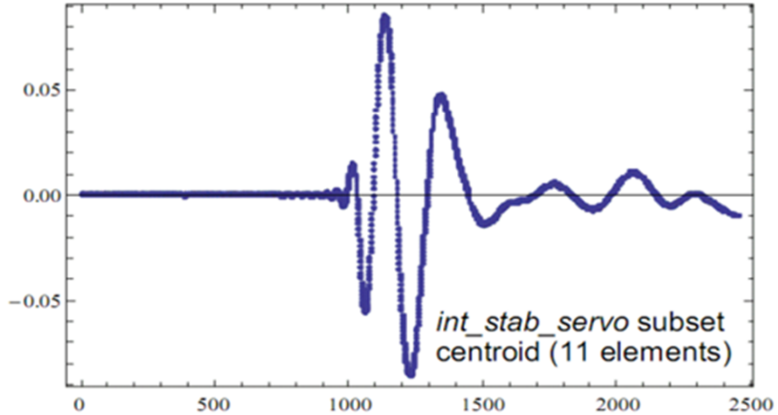
Hints from Glitch Clustering

The number of clusters N_c is usually found to be comparable to the embedding dimension N^* .

In many cases, the cluster-centroid waveforms are found to be almost *coincident with glitches whose origin is known*, obtained by "hammering" some *specific* instrument input-port.

This is *suggestive* that *glitch cluster centroids may correspond* to the *sought* proto-glitches $h_i^{(0)}(t)$.





[I.M. Pinto, L. Troiano et al., Int. J. Mod. Phys. C24 (2013) 1350084]

Beyond PCA

- Arguably, the key requirement of a "natural" glitch dictionary $\mathcal{D}_{\boldsymbol{\pi}} = \{\boldsymbol{\pi}_i | i = 1,2, \dots, P\}$ would be to allow to represent each glitch in the dataset $\mathcal{D}_{\mathbf{g}} = \{\boldsymbol{g}_i | i = 1,2, \dots, G\}$ using a *minimum number of elements from* $\mathcal{D}_{\boldsymbol{\pi}}$.

- Let $\boldsymbol{D}_g$ the *N x G* matrix whose columns are the $\boldsymbol{g_i}$ vectors, $\boldsymbol{D}_\pi$ the *N x P* matrix whose columns are the $\boldsymbol{\pi}_i$ vectors, and $\boldsymbol{D}_\alpha$ the *G x P* matrix whose elements are the representation coefficients $\alpha_{mn} = (\boldsymbol{g}_m, \boldsymbol{\pi}_n)$. Then, the above requirement can be written:

$$min \|\boldsymbol{D}_\alpha\|_0 \text{ subject to } \left\|\boldsymbol{D}_g{}^T - \boldsymbol{D}_\alpha \cdot \boldsymbol{D}_\pi{}^T\right\|_2 < \varepsilon$$

which is , technically, a *sparse(st) coding problem*.

- The above L_0 (constrained) optimization problem is *NP-hard,* but under broad assumptions, *it can be transformed into a convex L_1 optimization problem* [D.L. Donoho et al., PNAS 100 (2003) 2197].

Sparse Coding

- When the dictionary is *given in advance*, sparse coding can be implemented via "pursuit" algorithms, of which several flavors exist [D.L. Donoho et al., PNAS 100 (2003) 2197].
- In our case, we would like to *find out* the "best" or natural dictionary *as part of our sparse(st) representation problem*.
- This can be implemented **efficiently** by iterative algorithms that switch between **sparse - coding** (using a *given* dictionary), and **adaptive dictionary -updating** (based on *clustering*) .
- Such algorithms (known as k-SVD) can be regarded as *imple-menting a BSS on the given glitch dataset*.

[Kreutz et al., Neural Comp. 15 (2003) 349;
Aharon et al., IEEE T-SP 54 (2006) 4311]

The Best Model of a Cat ?

- It is further arguable that the sought "natural" *dictionaries* are *closest* to the speculated $\{\mathrm{h}_{0p}(t) \mid p = 1 \ldots M\}$ proto glitch sets .

In the words of Norbert Wiener, *"the best model for a cat is another cat, or preferably, the same cat."*

Norbert Wiener (1894-1964)

Neko San

Outlook

Glitch Busting

Assembling Glitch Databases

Glitch Enthomology

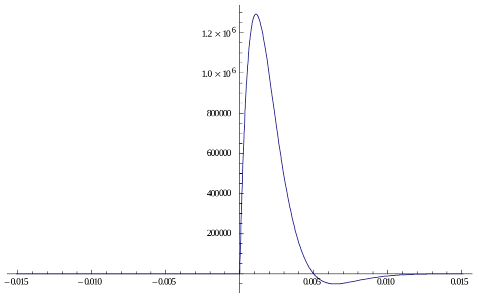
Glitchy Noise Modeling

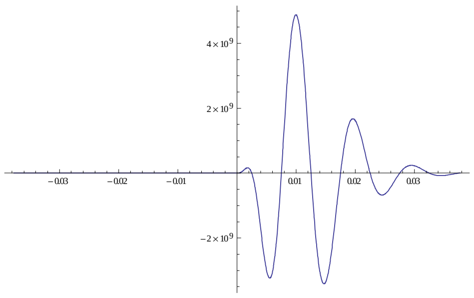
A Simple, Physically Driven Model

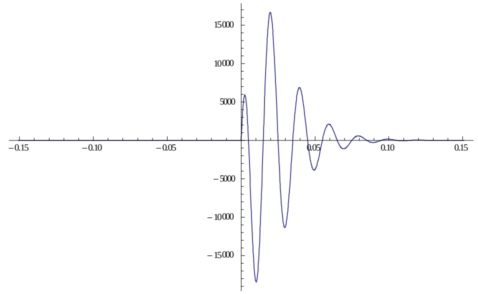
Proto Glitches, PCA, and Beyond

➡ Ongoing Work

WiP - Linear Modes



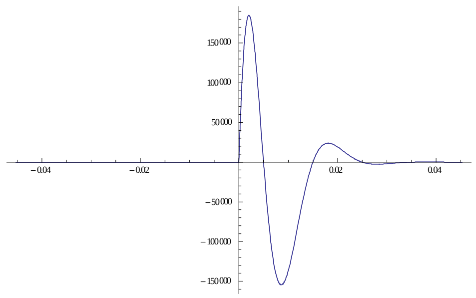


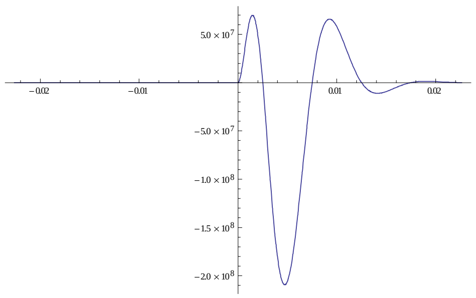


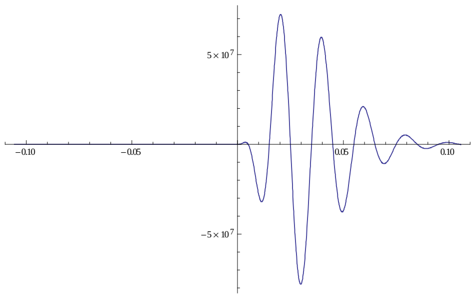
… the ingredients of the impulse response of LTI systems

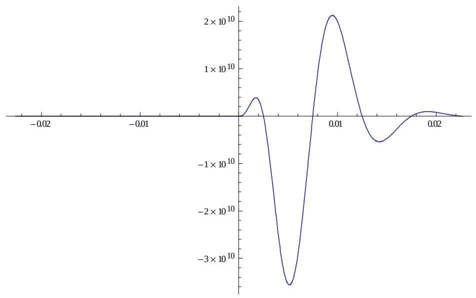
$$\psi(t;A,\theta,q,\alpha,\omega,\varphi) =$$
$$= AU(t-\theta)(t-\theta)^q \cdot$$
$$\cdot \exp[-\alpha(t-\theta)] \cdot$$
$$\cdot \cos[\omega t + \phi] \cdot$$

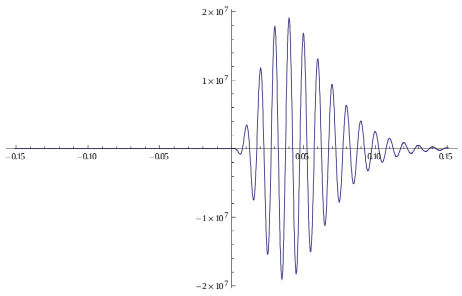
(6 free parameters, $q \in \aleph$)











WiP - Mock Data Tests

- *Linear modes* (and linear combinations thereof) are the *simplest meaningful choice* for simulating *proto-glitches ;*
- *Generate a (finite) dictionary of waveforms* $\mathfrak{D}_{\mathbf{g}} = \{\boldsymbol{g}_i | i = 1,2, \dots, G\}$ from random realizations of the *shape* parameters (q, α, ω, φ) in the above linear modes,
- Generate $N > G$ time series $\{\boldsymbol{s}_k | k = 1,2, \dots, N\}$ featuring the above dictionary elements, *with random amplitudes* (A) *and time-locations* (θ) (mock glitchy data) .
- Add (stationary, white) Gaussian noise with given variance(s) to the above time series.
- Test BSS algorithms' performance in retrieving the the dictionary $\mathfrak{D}_{\mathbf{g}} = \{\boldsymbol{g}_i | i = 1,2, \dots, G\}$ from the mock data $\{\boldsymbol{s}_k | k = 1,2, \dots, N\}$
- Next step will be to use real (Virgo VSR4, LIGO S5) data.

Conclusions

ありがとうございました

Thank you for your kind attention and patience!

Next Move is up to You!