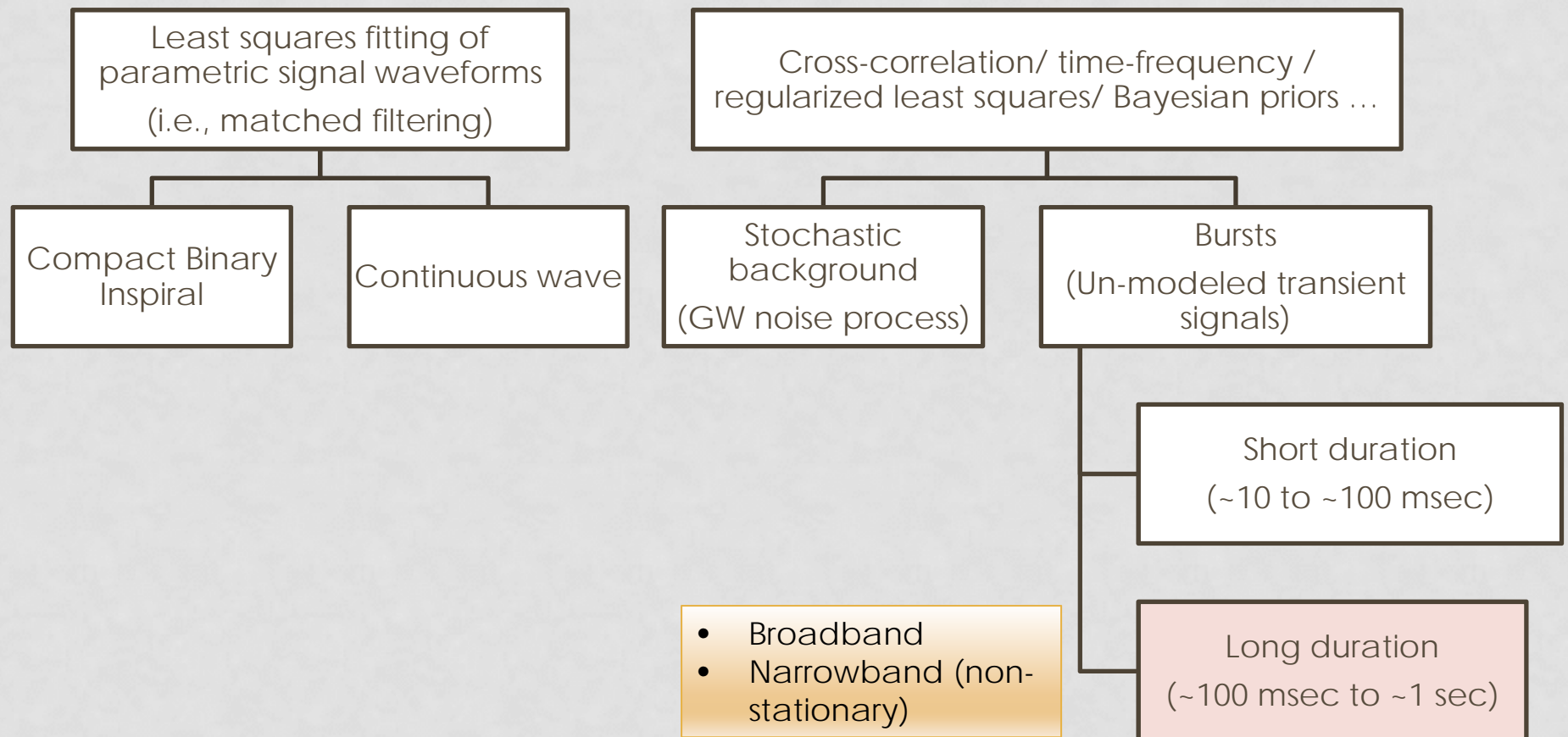


Un-modeled Narrowband Transient Gravitational Wave Signals

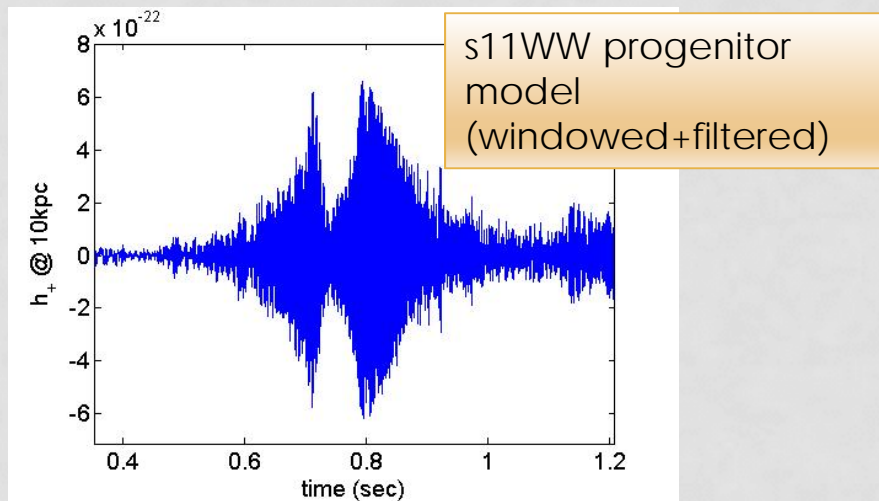
*Meeting the detection and
Estimation challenge*

Soumya D. Mohanty
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Center for Gravitational Wave Astronomy
UT Brownsville

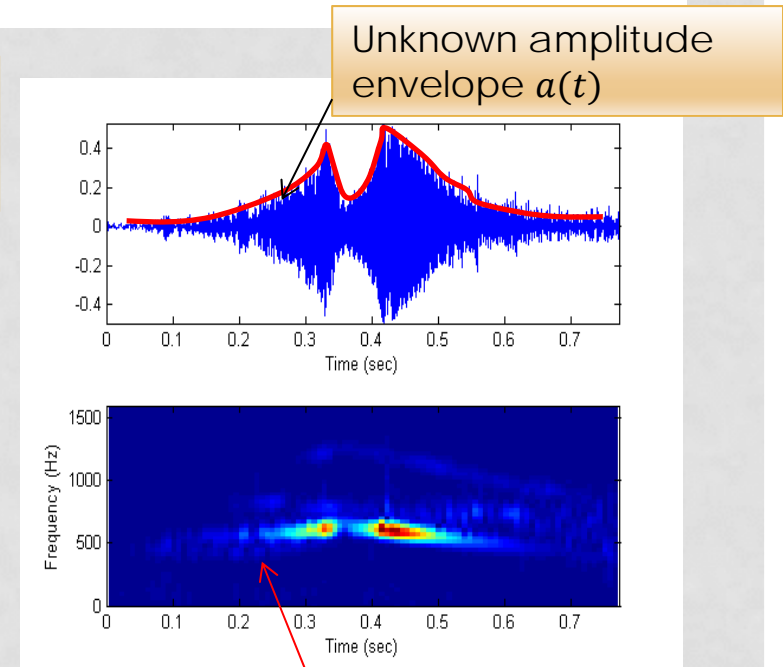
GW DATA ANALYSIS METHODS



UN-MODELED NARROWBAND TRANSIENT GW SIGNALS



Acoustic mechanism for shock revival in post-bounce phase of a core collapse supernova (CCSN).
-- Ott et al, Phys. Rev. Lett. (2006)



$$s(t) = a(t) \cos(\varphi(t))$$

$a(t)$ is an unknown amplitude envelope; $\varphi(t)$ is an unknown phase

Narrowband: $a(t)$ and instantaneous frequency, $\dot{\varphi}(t)$, change over much longer timescales than the instantaneous period ($2\pi/\dot{\varphi}$)

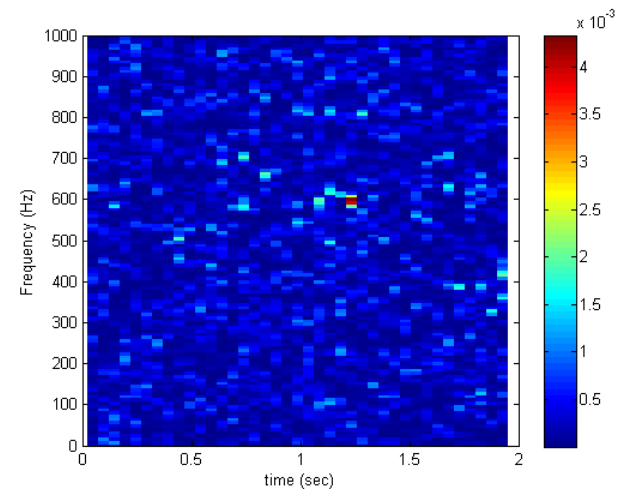
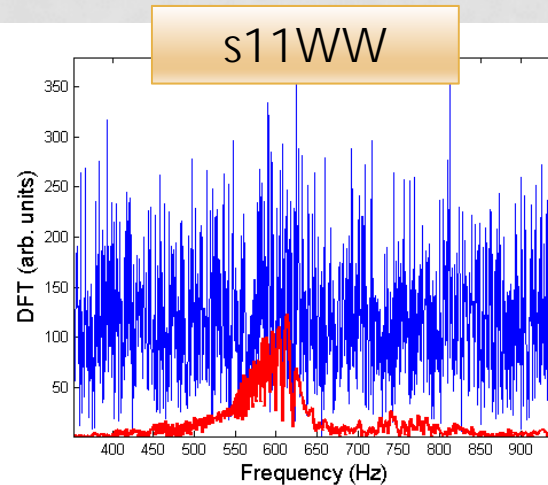
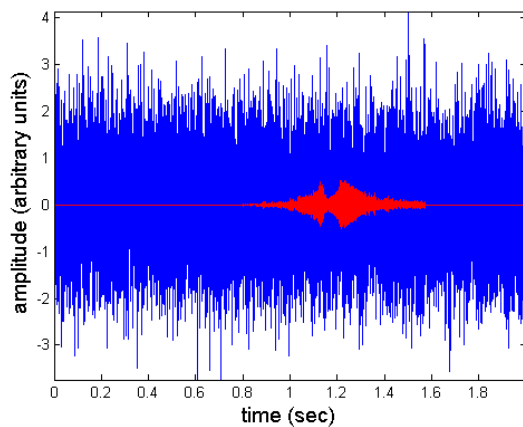
Non-stationary: Instantaneous frequency can evolve over a large range

- Instabilities in collapsar BH accretion torus (van Putten, Phys. Rev. D (2004))
- Crustal modes of Magnetars (Murphy et al, Phys. Rev. D (2013))

THE CHALLENGE

Advanced LIGO Matched filtering Signal to Noise Ratio (SNR) @ 10 kpc is in the range 5 to 20 for most long duration CCSN signals with optimal source and detector orientation . (Murphy *et al. ApJ* (2009))

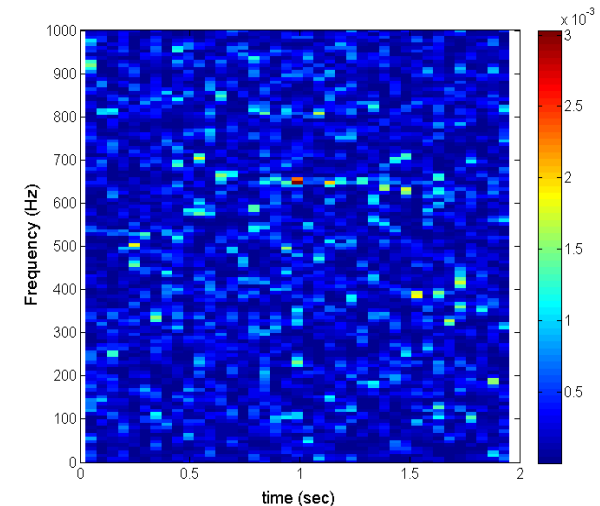
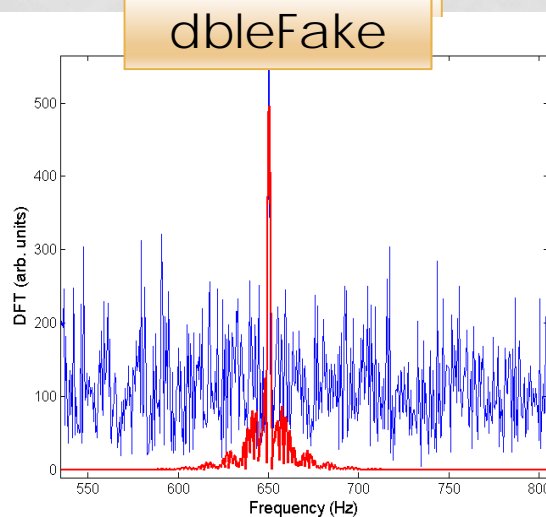
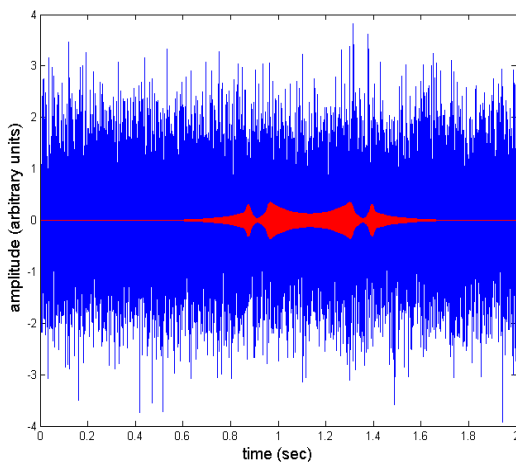
We consider SNR=10 signals in white Gaussian noise.



THE CHALLENGE

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We consider SNR=10 signals in white Gaussian noise.



Detection Challenge: Detect signal at a fairly low false alarm probability

Estimation Challenge: Estimated signal should match true signal in at least some characteristic features

Time-frequency methods are ineffective, especially for estimation

ALGORITHM

\bar{y} data vector $\in R^N$ and \bar{s} signal vector $\in S \subset R^N$

\bar{s} : samples of the analog signal

$$s(t; \bar{\tau}, \bar{\psi}) = a(t; \bar{\tau}) \cos \phi(t; \bar{\psi})$$

$a(t; \bar{\tau})$: cubic spline with knots at $\bar{\tau} = (\tau_1, \tau_2, \dots, \tau_M)$

$$\Rightarrow a(t; \bar{\tau}) = \sum_{i=1}^M \alpha_i \times \underbrace{B_i(t; \bar{\tau})}_{\text{Basis Functions of the linear space of cubic splines with knots at } \bar{\tau}}$$

Enforces smoothness of $a(t)$

Basis Functions of the linear space of cubic splines with knots at $\bar{\tau}$

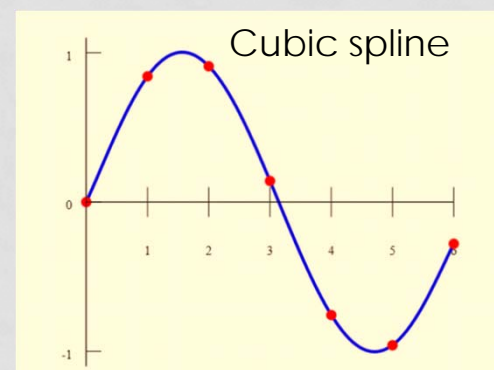
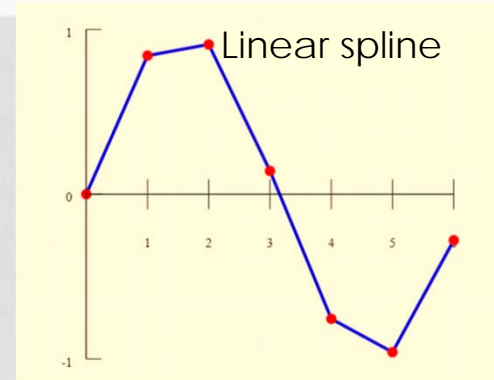
$$\phi(t; \bar{\psi}) = \int_0^t f(t'; \bar{\psi}) dt'$$

$f(t; \bar{\psi})$: linear spline with knots at $\bar{\psi} = (\psi_1, \dots, \psi_K)$

Minimize over $\bar{\tau}, \bar{\psi}, \{\alpha_i\}, i = 1, \dots, M$

$$\underbrace{L(\bar{\tau}, \bar{\psi}; \bar{y})}_{\text{Fitness function}} = \underbrace{\| \bar{y} - \bar{s}(t; \bar{\tau}, \bar{\psi}) \|^2}_{\text{Standard MLE functional}} + \lambda \underbrace{\sum_{i=1}^M \alpha_i^2}_{\text{Penalty term}}$$

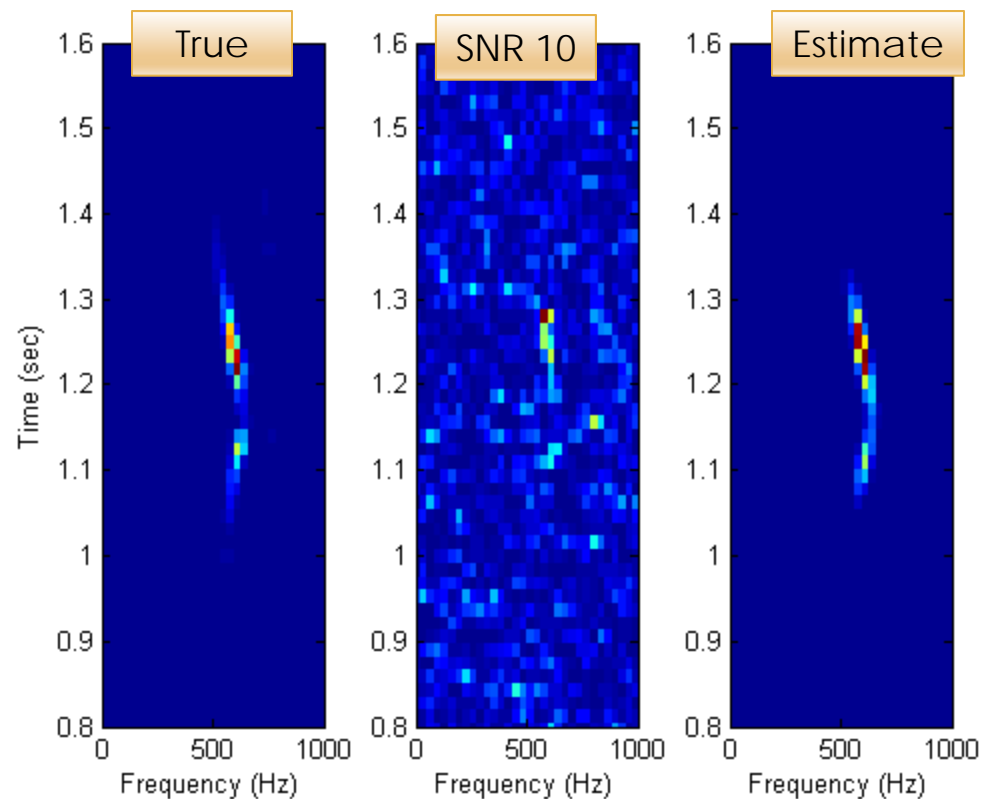
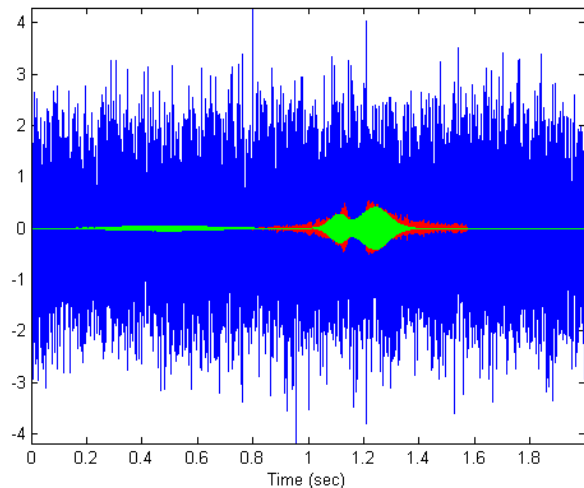
Rupert, Wand, Carroll, *Semiparametric Regression*



- α_i solved analytically for given $\bar{\tau}$ and $\bar{\psi}$
- Minimization over $\bar{\tau}$ and $\bar{\psi}$: Particle Swarm Optimization (Kennedy, Eberhart, 1995)

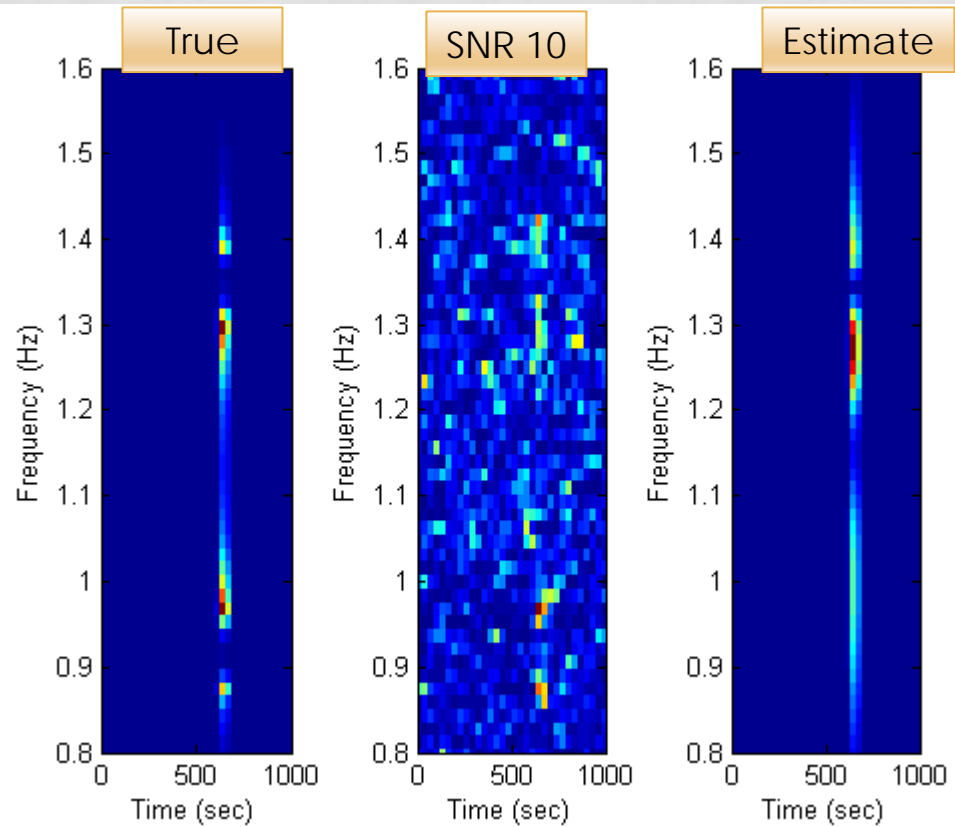
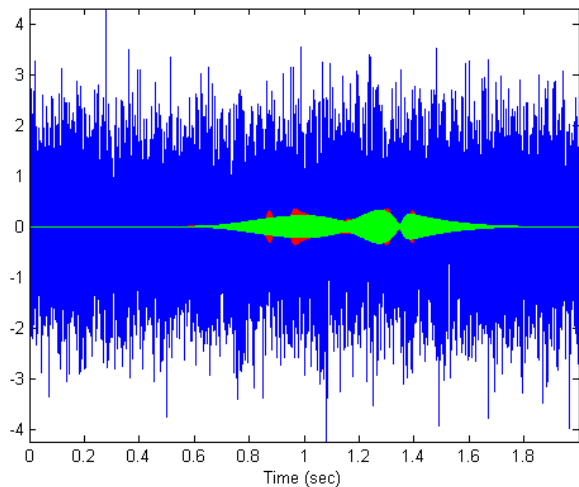
EXAMPLES

- Data length 2 sec; 10 temporal and 5 frequency knots+5 frequency values
- PSO based optimization over a 20 dimensional search space
- Max. instantaneous signal frequency for the search : 800 Hz.



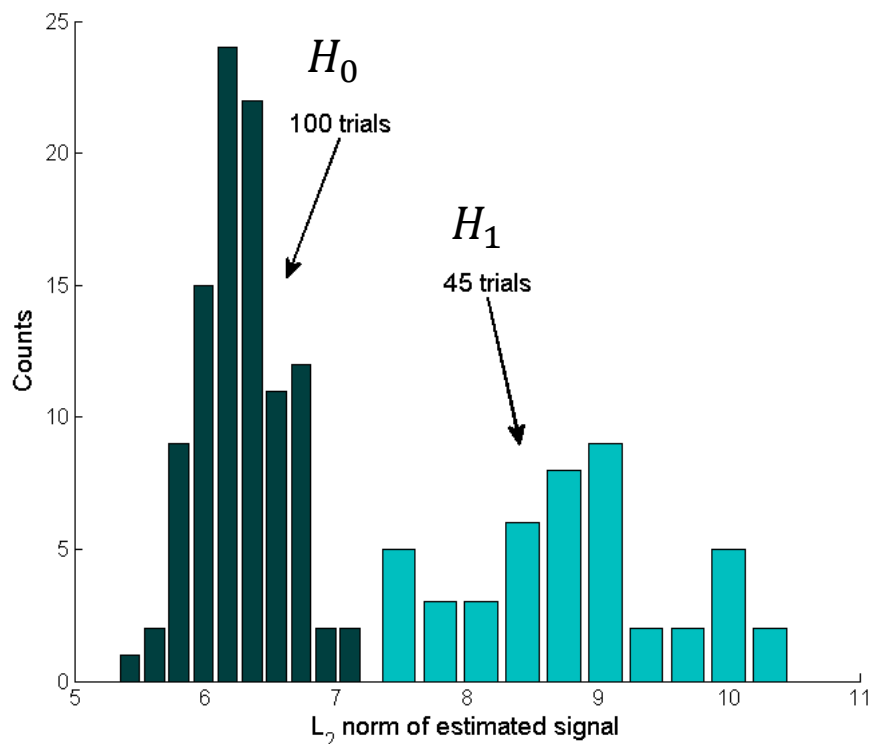
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RESULTS: DETECTION PERFORMANCE

White Gaussian noise;
s11WW @ matched filtering SNR = 10
Detection statistic (λ): L_2 -norm of estimated
signal



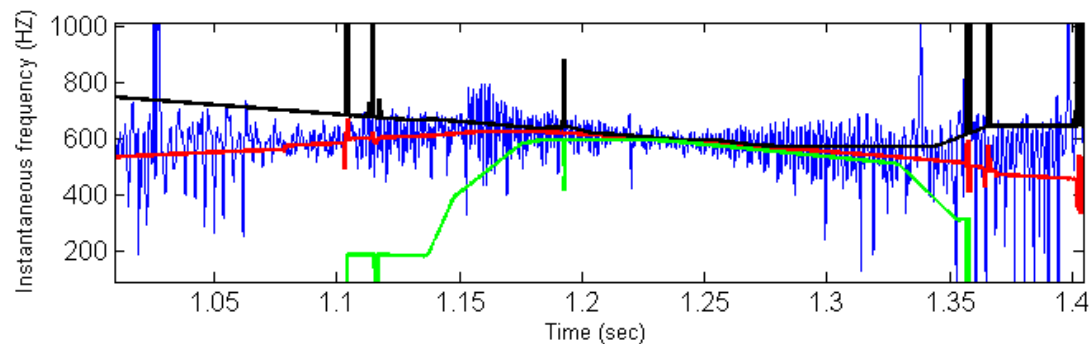
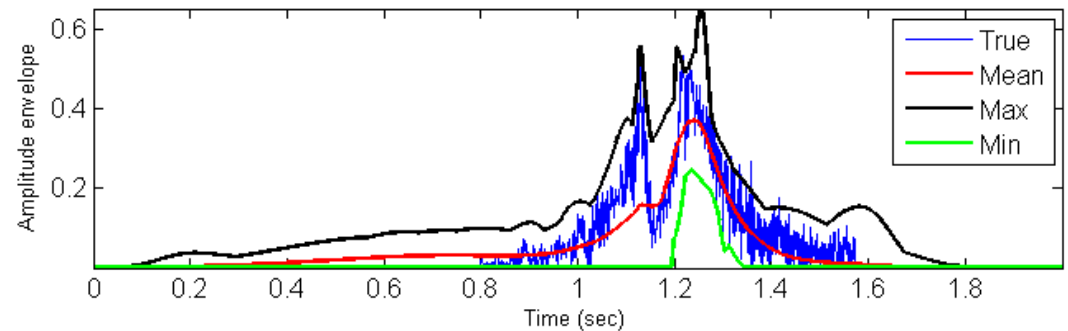
$$\text{Effective SNR} = \frac{\text{mean}(\lambda|H_1) - \text{mean}(\lambda|H_0)}{\text{stdev}(\lambda|H_0)}$$

- s11WW signal: 7.6
- dbleFake signal: 10.6 (\approx matched filtering SNR!)
- Plain Time-frequency method with hand-tuned TF parameters.
- λ : magnitude of the loudest pixel in:
 - H_0 : [0, 800] Hz and [0, 2.0]sec
 - H_1 : [500,700]Hz and [0.8,1.5]sec
 - s11WW signal: 5.5
 - dbleFake signal: 5.4

ESTIMATION PERFORMANCE

- Sample-by-sample match of true and estimated signals is not a useful measure of estimation performance
- We need to know how well some basic features are estimated .

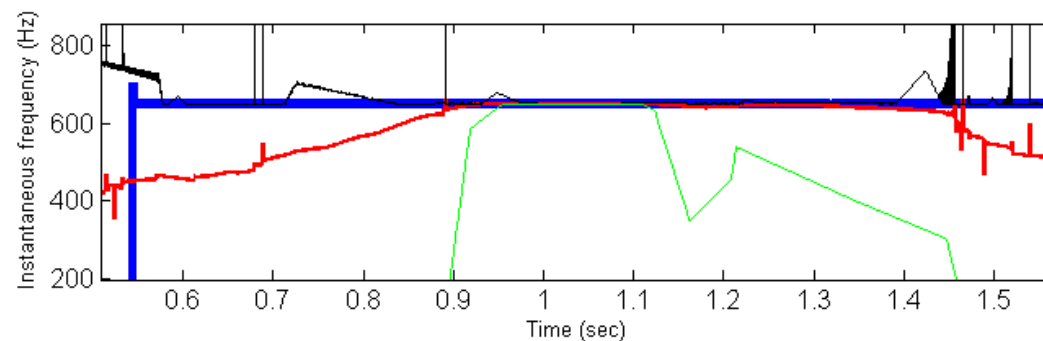
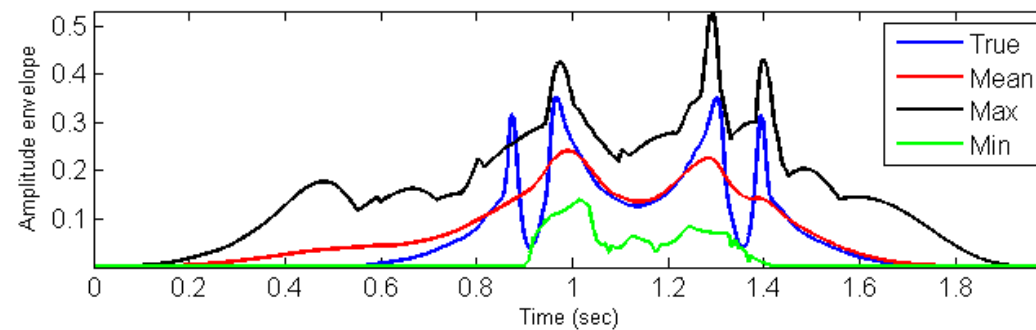
Amplitude envelope and instantaneous frequency of the **analytic representation of the signal** (Hilbert transform)



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Amplitude envelope and instantaneous frequency of the **analytic representation of the signal** (Hilbert transform)



SUMMARY

- A GW search algorithm for situations where time-frequency methods don't work well
 - At best, TF analysis misidentifies a long duration signal as a short burst
- Can resolve widely different amplitude and carrier frequency evolutions
 - Good match of the estimated amplitude envelope and instantaneous frequency on the average
 - Better discrimination of source models in terms of their GW signals
- Detection performance is fairly robust across the wide range of signals considered
 - Effective SNR between 7.5 and 10.0 for matched filtering SNR of 10
- Work in progress on further improvements
 - Improving the non-linear optimization phase (currently using PSO with minimal modifications)
 - Instantaneous frequency models that show smoother time evolution.