Improving the LIGO CBC Search Pipelines

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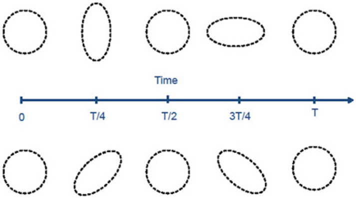
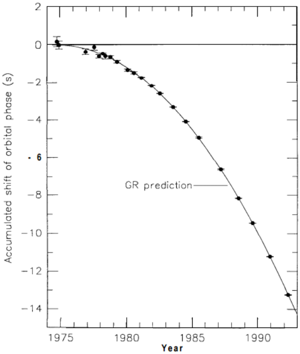
Gravitational Waves

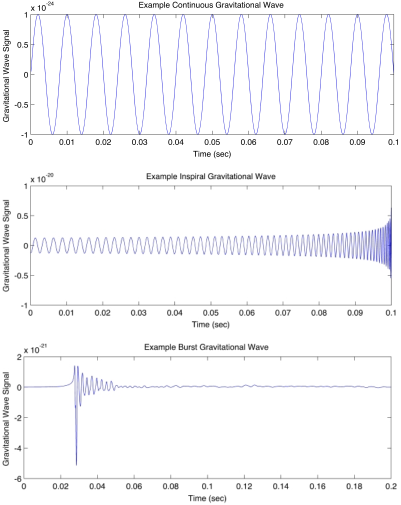
- Gravitational waves (GW) first predicted by Einstein in 1916.
- Two polarizations: h_+ and $h_\times$.
- Travel at the speed of light.
- Strong evidence for their existence:
  - Hulse and Taylor noticed radiative losses in a binary pulsar system
  - Matched predictions from general relativity
- No direct detection of GW has been made because the signals are very weak.





Graviational Wave Sources

- GW are generated by a mass quadrupole moment.
- Contrast with electromagnetic sources which only require a dipole moment.
- Example GW sources:
  - Compact Binary Coalescence
  - Continuous Waves
  - Bursts (e.g. Supernovae)
  - Stochastic (Primordial) GW



Top: Continuous Wave, Center: Inspiral, Bottom: Burst

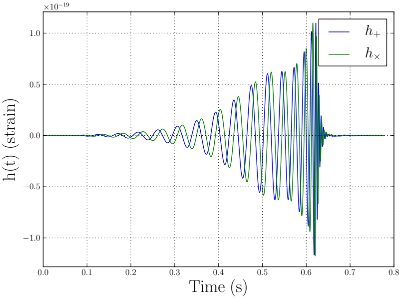
THE LIGO DETECTORS

- The LIGO detectors are Michelson interferometers with 4 km arms.
- One is located in Livingston, LA and the other is in Hanford, WA.
- Laser light is bounced back and forth many times in the arm cavities.
- A passing gravitational wave will alter the relative path length for light in the two arms.
- The change in arm length can be read out as a GW after calibration.
- Sophisticated techniques are used to account for sources of noise.

Top: LIGO Hanford,
Bottom: LIGO Livingston

Compact Binary Sources

- Compact binary systems are important sources for LIGO.
- These systems are a natural place to search:
  - We know that they exist
  - They have large mass quadrupole moments
  - The waveforms are relatively well-understood
  - They allow for tests of GR in a very dynamic regime



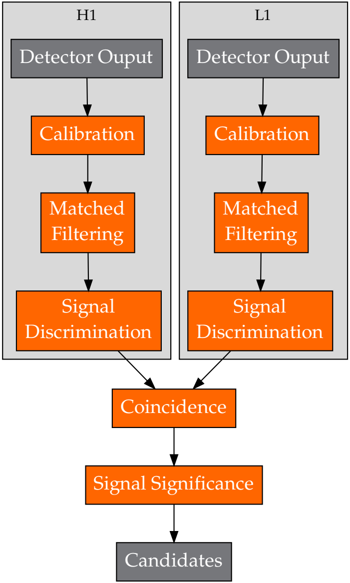
Time domain waveforms for two non-spinning 50 $M_\odot$ black holes.

Project Goals

- This project seeks to optimize the `gstlal` pipeline used in compact binary coalescence (CBC) searches
- I will discuss optimizations in both the speed and sensitivity of the search pipeline
- Specifically, I will discuss:
  1. A faster stochastic template bank algorithm
  2. Attempts to optimize the autocorrelation χ^2 test

Search Pipelines

- CBC searches utilize data analysis pipelines
- I will talk specifically about the `gstlal` pipeline
- Generally, the pipeline flow is:
  1. Calibration of data
  2. Matched filtering
  3. Signal discriminator tests (χ^2)
  4. Detector network coincidence
  5. Signal significance, false alarm rate
- Noise triggers are suppressed
- Events which survive all these steps are candidates



Search Pipelines

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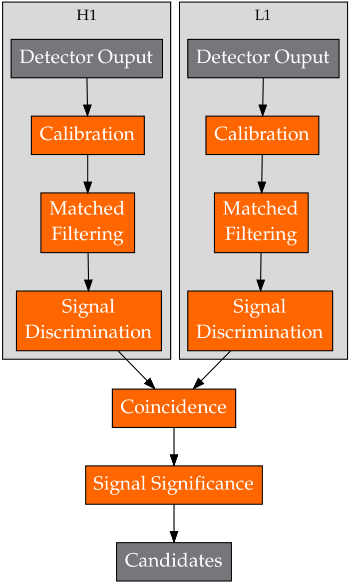
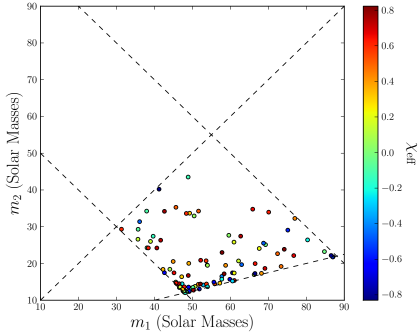


Template Banks

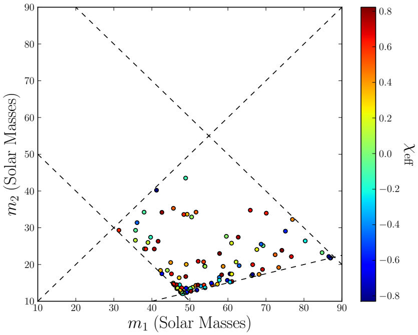
- Data must be filtered using a discrete template bank
- For low-dimensional parameter spaces, metric methods can be used to construct banks [1]
- For inspiral-only templates in the 2D mass space, an optimal method exists [2]
- For more complicated cases, analytical methods don't exist
- In these cases, stochastic methods are necessary [3]



A template bank for an aligned spin, high mass parameter space.

Stochastic Template Banks

- The standard stochastic template bank algorithm has two main drawbacks:
  1. The match between templates is not Cartesian in standard coordinate systems (i.e. the masses).
  2. There is a bottleneck when placing the last few templates.



Stochastic Template Banks

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- The first problem has a simple solution: choose a better coordinate system.
- Typically the chirp time coordinates τ_0, τ_3 are used because the metric is almost flat in them [4].
- The chirp time coordinates are contributions at different PN orders to the amount of time for the binary to coalesce.

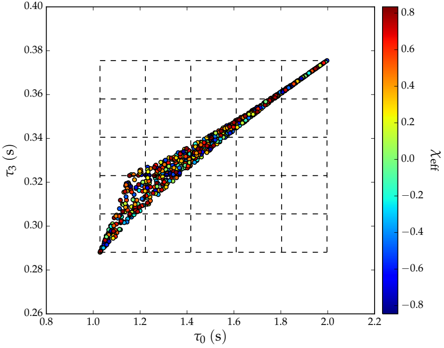
Stochastic Template Banks

- The standard stochastic template bank algorithm has two main drawbacks:
  1. The match between templates is not Cartesian in standard coordinate systems (i.e. the masses).
  2. There is a bottleneck when placing the last few templates.
- This second problem is inherent to the algorithm used.
- Without knowledge of where templates were previously placed, it is impossible to avoid this bottleneck.

New Stochastic Algorithm

- The new algorithm keeps track of where templates have been placed
- The parameter space is gridded and in each cell, two numbers are tracked:
  - The number of accepted templates A_i
  - The number of rejected templates R_i
- The probability of placing a template in a cell is:

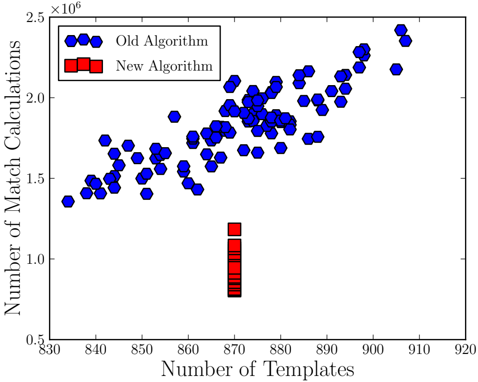
$$P_i = \frac{A_i}{A_i + R_i}$$

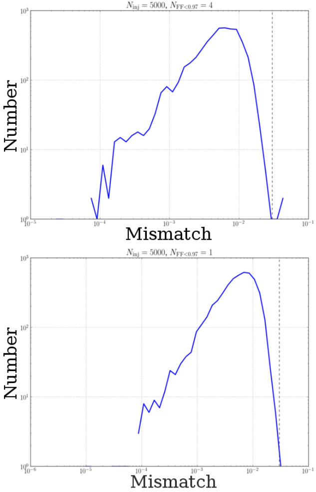


Example parameter space grid.

Performance of New Algorithm

The new algorithm requires far fewer match calculations and produces banks of equal quality.



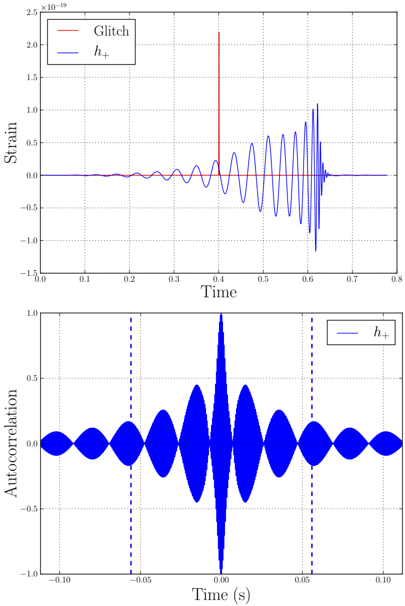


Old (top) vs. New (bottom)

χ^2 Tests

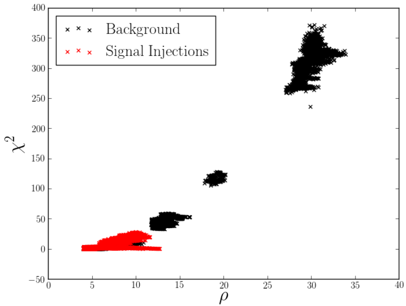
- Non-gaussian noise (glitches) is a constant problem
- Signal consistency tests (χ^2 tests) are used to reject glitches
- Many such tests have been developed [5, 6]
- I will describe changes to the autocorrelation χ^2 given by:

$$\chi^2 = \int_0^{T_{\max}} |\rho(\tau) - \rho_{\text{peak}}\alpha(\tau)|^2 d\tau$$

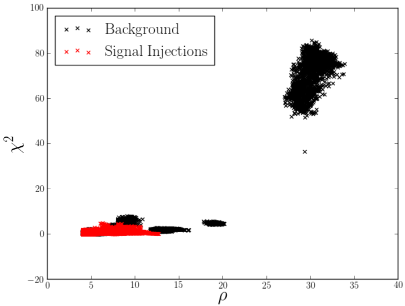


Windowing in Autocorrelation Power

Results for the autocorrelation χ^2 computed in a window of 90% autocorrelation power.



Old χ^2



Modified χ^2

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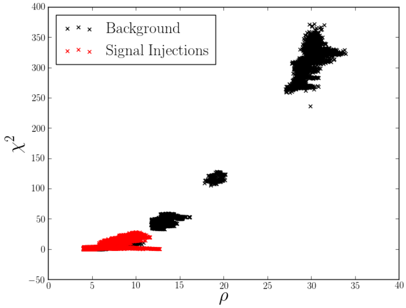
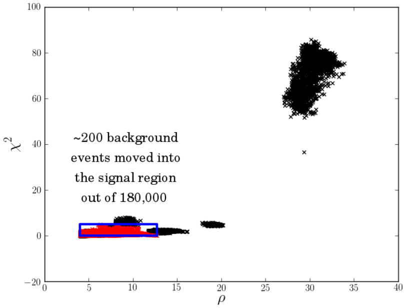


Old χ^2

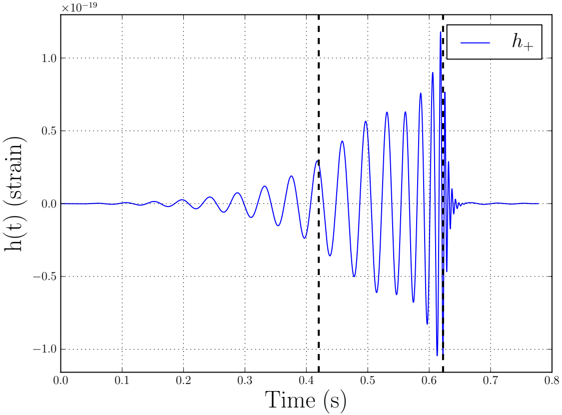


Modified χ^2

This method contaminates the signal population with background events and thus cannot be used.

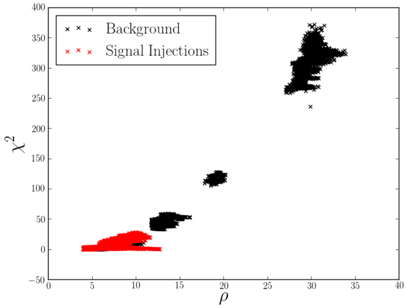
Windowing in Template Power

Another option is to compute the autocorrelation χ^2 in a window determined by the region of highest template power.

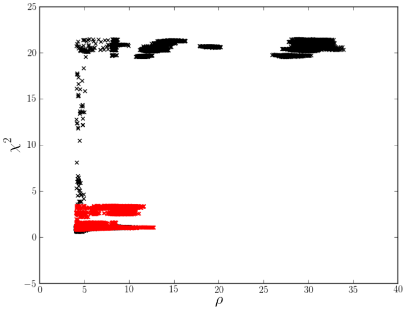


Windowing in Template Power

Results for the autocorrelation χ^2 computed in a window of 90% template power.



Old χ^2



Modified χ^2

Windowing in Template Power

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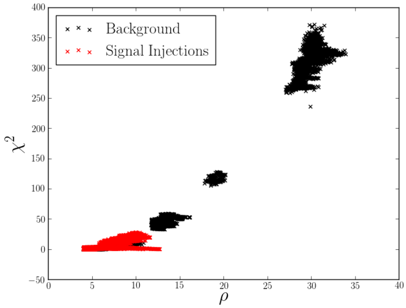
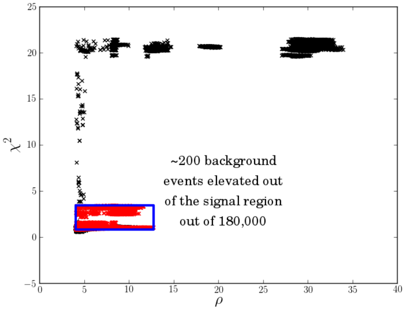


Old χ^2



Modified χ^2

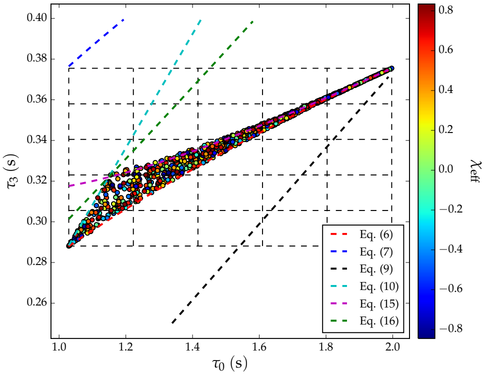
This method elevates the χ^2 of contaminating background events, but not to a significant degree.

Conclusions

- It is possible to construct a computationally efficient stochastic template bank algorithm using acceptance-rejection methods.
- This new algorithm produces banks of equal quality to standard methods.
- A framework for making the autocorrelation length adaptive was developed and can be used to alter pipeline performance.
- Making the autocorrelation length adaptive can yield small changes to the signal-background separation.

Future Work

- In the future, work could be done to:
  1. Analytically compute the τ_0, τ_3 boundaries to make the acceptance-rejection sampling faster.
  2. Tune the power intervals for the autocorrelation χ^2 so that better performance can be achieved.



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τ_0, τ_3 COORDINATES

τ_0 and τ_3 are the contributions to the chirp time at Newtonian and 3PN order respectively. They are given by:

$$\tau_0 = \frac{5}{256\pi f_L \eta}(\pi M f_L)^{-5/3}$$
$$\tau_3 = \frac{1}{8 f_L \eta}(\pi M f_L)^{-2/3}$$

where $\eta = m_1 m_2 / M^2$ is the symmetric mass ratio, $M = m_1 + m_2$ is the total mass, and f_L is the lower bound on the frequency of the waveform.

They give a nice, flat coordinate system for template placement.

Full Stochastic Algorithm

Let $\mathcal{M}$ be a signal manifold of dimension D with a positive-definite distance $d(x, y)$ where $x, y \in \mathcal{M}$. A template bank T is a set of n points $\{x_1, \ldots, x_n \mid x_i \in \mathcal{M}\}$. T covers the signal manifold $\mathcal{M}$ with radius Δ if $\forall\, y \in \mathcal{M},\ \exists\, x_i \in T$ such that $d(x_i, y) < \Delta$. Then the algorithm proceeds as follows:

1. Cover $\mathcal{M}$ with k^D equally sized bins $B_i,\ i = 1, \ldots, k^D$ where k is the number of divisions per dimension. To construct the bins:
   - 1.1 Suppose the binary source parameters are given by $\theta_i, i = 1, \ldots, D$ and that each parameter takes values in the interval $[\theta_{i,min}, \theta_{i,max}]$ on $\mathcal{M}$. Divide this interval into k equal length sub-intervals $\theta_{i,\alpha}$ where $\alpha = 1, \ldots, k$.
   - 1.2 Each bin is then given by the Cartesian product $\theta_{1,\alpha} \times \theta_{2,\beta} \times \ldots \times \theta_{D,\omega}$ where all the greek indices go from 1 to k.

Full Stochastic Algorithm (cont.)

2. For each bin B_i, assign two values: the number of accepted templates A_i and the number of rejected templates R_i. Initially these values are set to $A_i = 1, R_i = 0$ although other choices are possible.
3. Choose a proposal template y uniformly from the signal manifold and determine which bin, B_i it falls into. Then compute the rejection probability P_i for that bin given by:

$$P_i = \frac{R_i}{R_i + A_i}$$

4. Choose a random number r uniformly from $[0, 1]$. If $r < P_i$, discard y and return to step 3.
5. If $d(y, x_i) > \Delta \; \forall \; x_i \in T$, add y to T. Otherwise, discard y and return to step 3.
6. Continue 3-5 until $P_i > P^* \; \forall \; i$ where P^* is a cutoff probability that can be varied to change the performance of the algorithm.

Autocorrelation χ^2

Suppose that the detector output is of the form $x(t) = n(t) + Ah(t)$ where A is some amplitude and h is unit-normalized so that $(h|h) = 1$. Then, the SNR time series is:

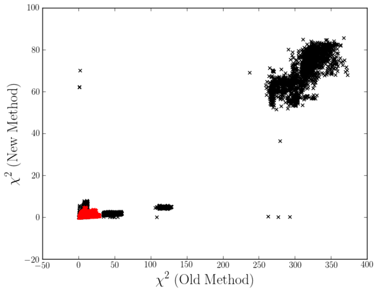
$$\begin{aligned}\rho(\tau) &= (n|he^{2\pi i f \tau}) + A(h|he^{2\pi i f \tau}) \\ &= (n|he^{2\pi i f \tau}) + \alpha(\tau)\end{aligned}$$

where $\alpha(\tau)$ is the autocorrelation of the template. Maximizing in time and taking an ensemble average so that the noise term disappears gives $\langle \rho_{max} \rangle \approx A$. The quantity $(n|he^{2\pi i f \tau})$ will be Gaussian distributed when the noise is Gaussian. Thus, it is possible to compute a χ^2 of the form

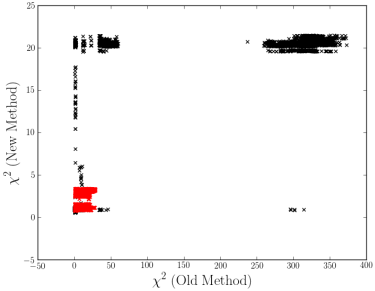
$$\chi^2 = \int_0^{T_{\max}} |\rho(\tau) - \rho_{\max}\alpha(\tau)|^2 d\tau.$$

χ^2 vs. χ^2 Plots

Comparing the χ^2 between the standard calculation and the two modifications gives a sense of their performance.



Autocorrelation Power



Template Power