A novel method for detecting coalescing binaries in near realtime with Advanced LIGO and beyond

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Abstract. Conventional matched filter bank methods for the detection of gravitational waves from the inspiral of compact binaries are computationally expensive, have hundreds of seconds of unavoidable intrinsic latency, and require arrays of largely redundant matched filters. Novel detection methods that are more computationally efficient and have lower latency will be required to realize the full potential of advanced of gravitational wave detectors that are currently under construction. In this paper, we describe a new detection method that exploits the properties of inspiral waveforms using multi-rate filtering, principal component analysis, and hierarchical detection. We provide receiver operating characteristics from a prototype search pipeline that is capable of low-latency or near-realtime detection with greatly reduced computational requirements in comparison with previously described methods.

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1. Introduction

Low-mass inspiraling binaries are the most promising sources of gravitational radiation for Advanced LIGO. Observation demonstrates that they must exist in the local Universe in some abundance [1]. [science] In the final stages of inspiral, the neutron star is tidally disrupted, providing the matter required to produce bright electromagnetic counterparts [2]. Conveniently, the gravitational waveforms are understood and implemented to the level required by Advanced LIGO to detect [3], allowing the sensitive technique of matched filtering.

The parameter space of compact binary coalescence signals is large [4, 5] leading to large filter banks and significant computational cost. Following the series of detector upgrades that are now under way, LIGO and Virgo will attain their Advanced configurations, gaining a tenfold improvement in amplitude sensitivity over Initial configurations [6, 7] and a corresponding thousandfold increase in observable volume in the local Universe. The computational requirements of conventional detection strategies will be greatly increased by this upgrade for two reasons. First, advanced detectors will have much improved low-frequency sensitivity, so chirp signals from coalescing binaries will remain in the detectors' band for a significantly longer time. This will demand that matched filter based searches use longer templates, requiring more memory and more cycles to process. Second, background noise for advanced detectors will be more spectrally uniform, so it will be possible to resolve the intrinsic parameters of a source that determine the time-frequency structure of the gravitational wave signal with much greater accuracy. This will require that matched filter bank based searches employ more matched filters, again demanding more memory and more cycles.

Beyond raw throughput, the ability to detect signals in near realtime will become increasingly valuable as the gravitational-wave detection horizon pushes outward. Having an electromagnetic or neutrino counterpart to a gravitational-wave detection would not only increase the confidence in the detection but will also greatly increase the astrophysical information available from the event. Most models that predict simultaneous gravitational-wave and electromagnetic observations also predict that the peak amplitude of electromagetic radiation will occur soon after gravitational-wave emission [8]. Thus in order to maximize the chance of a successful electromagnetic followup the latency of gravitational-wave signal analysis must be made minimal.

In 2010, LIGO and Virgo completed S6/VSR3, a short period of joint data taking during which several all-sky detection pipelines operated in a low-latency configuration [CITATION NEEDED]. A few candidates of moderate significance were promptly sent for electromagnetic followup [CITATION NEEDED] to several telescopes including Swift, ROTSE, TAROT, and Zadko. They achieved latencies of BLAH, but required human vetting of each candidate before alerting the telescope partners. As confidence in the infrastructure increases, humans can be removed from the loop, setting a demonstrated previous best latency at BLAH.

This work will describe how to exploit degeneracy in the signal parameter space to answer more quickly and economically whether or not a gravitational wave is present. Specifically, we will exploit the time-frequency structure of chirp signals to downsample different parts of the waveform, use the singular value decomposition (SVD) factors to identify the redundancy of the bank and reduce the effective number of filters required to search the data, and use matched subspace filters built from SVD to identify when computation can be avoided. We note that others have applied the use of SVD to gravitational wave data analysis to analyze optimal gravitational-wave burst detection [9, 10] and coherent networks of detectors [11].

nvf: I use some rather different words here to summarize the techniques. I don't want to simply repeat words from later, but I don't want to jar a reader with changing jargon either. Feel free to edit.

The paper is organized as follows. First we provide an overview of the standard method for detecting compact binary coalescence signals and describe how it can be modified to accomodate low latency analysis. We then describe the pipeline we have constructed to implement these changes. To validate the approach we present results of simulations and finish with some concluding remarks.

2. Method

2.1. The standard approach: matched filtering

Searches for gravitational waves from compact binary coalescences typically employ matched filter banks [12]. Potential inspiral signals are continuously parameterized by time, amplitude, phase, and a set of intrinsic source parameters θ, which in this paper we shall take to consist of the two component masses of a binary, $\theta = (m_1, m_2)$. Let $h_+(\theta)$ and $h_\times(\theta)$ be, respectively, the '+' and '×' polarization gravitational wave signals that would arise from a fiducial face-on binary at some distance. Because, for inspiral signals, h_+ and $h_\times$ are nearly in quadrature, they are generally combined into a single complex-valued template $h = h_+ + ih_\times$.

The detection procedure for just one set of intrinsic source parameters θ starts by *whitening* the measurement data stream x. This involves finding a linear filter that renders the detector's noise IID and Gaussian. This filter is applied to the measurement, yielding the whitened data stream x^{W}. The same linear filter is applied to the template $h(\theta)$, yielding the whitened template $h^{\mathrm{W}}(\theta)$. The matched filter is the normalized cross-correlation of h^{W} and x^{W},

After introducing the $\star$ notation for cross correlation, must we define it for continuous and discrete time?

$$\rho(\theta) = \frac{h^{\mathrm{W}}(\theta) \star x^{\mathrm{W}}}{|h^{\mathrm{W}}(\theta)|}.$$

This is called the signal to noise ratio, or SNR. The detection statistic is the modulus of this, $|\rho(\theta)|$, which has a χ^2 distribution with 2 degrees of freedom in the absence of signal.

To construct a filter bank, matched filters are realized for discrete signal parameters θ_1, θ_2, $\cdots$, θ_N, such that any possible signal will have a maximum cross-correlation of at least 0.97 with at least one template. Such a template bank is said to have a 97% *minimum match*. This technique is designed so that an inspiral signal can be detected without any prior knowledge of its intrinsic parameters: at most 3% of the SNR is lost by a signal's parameters not exactly coinciding with a template's. A trigger is reported for the template parameters θ_i and time t for which $|\rho|$ is a maximum over some moving interval in θ and t.

Citation needed for template placement procedure?

2.1.1. Latency and overhead The matched filter bank can be implemented with finite impulse response (FIR) filters. FIR filters are perfectly suited for realtime detection, because they do not introduce any latency at all. However, FIR filters are very expensive: for N templates of M samples each, a FIR matched filter bank costs $\mathcal{O}(MN)$ operations per sample.

Much more commonly, the matched filter bank is implemented using FFT convolutions, costing only $\mathcal{O}(M \lg N)$ per sample but having a latency of at least M samples. For example, for a bank of 1 ks templates sampled at 4096 Hz, the FFT implementation requires about about 2.2×10^4 times fewer floating point operations per sample than the FIR implementation. However, the FFT implementation has a latency of at least 1 ks.

lg *is* $\log_2$. *Explain nomenclature? Switch to* $\log_2$*?*

This presents a dilemma: it seems that low latency detection using the FIR implementation is prohibitively expensive, whereas computationally cheap detection with the FFT method comes with minutes to hours of latency.

In the rest of the section, we will describe a detection strategy that makes use of some very general properties of inspiral template banks in order to evaluate a matched filter bank with far lower computational cost than the FIR method and far less latency than the FFT method.

2.2. Selectively reducing the sample rate of the data and template waveforms

Our first innovation is to split each template into disjoint intervals, or *time slices*. A matched filter is constructed for each time slice, whose outputs form an ensemble of partial SNR streams. By linearity, these partial SNR streams can be suitably time delayed and summed to reproduce exactly the SNR with respect to the original template. By exploiting some general properties of inspiral waveforms, we shall see that time slices permit a reduction in latency relative to the FFT matched filter, but with comparable computational overhead.

A similar idea has been demonstrated by the Virgo Collaboration's MBTA pipeline [13, 14, 15, 16], which operated in a low-latency mode during LIGO's sixth science run and Virgo's second science run in 2010.

MBTA should be cited in the introduction.

Each partial matched filter can be realized with either the FIR or the FFT method. If all of the time slices make use of the FFT method, the resulting filter will have lower latency than a conventional FFT matched filter, and also less computational overhead than an FIR matched filter. A further benefit is that all of the time slices may be processed in parallel for additional speedup.

If the template is known to be quasi-bandlimited, then the partial matched filter for each time slice may be processed at a reduce sample rate. Compact binary inspiral waveforms fit this description superbly: they are chirps whose frequency and amplitude rise according to power laws of time. They are not only quasi-bandlimited, but quasi-monochromatic. By exploiting this property, we can implement a matched filter for an inspiral waveform using a multirate filter bank that requires far fewer floating point operations.

For concreteness and simplicity, let us consider an inspiral waveform in the quadrupole approximation, for which the time-frequency relation is

$$f = \frac{1}{\pi\mathcal{M}}\left[\frac{5}{256}\frac{\mathcal{M}}{-t}\right]^{3/8}. \tag{1}$$

Here, $\mathcal{M}$ is the chirp mass of the binary in units of time (where $GM_\odot/c^3 \approx 5\mu$s) and t is the time relative to the coalescence of the binary [12, 17, 18, 19]. Usually the template is truncated at some prescribed time $t = t_0$, often chosen to correspond to the innermost stable circular orbit at which $f = f_{\mathrm{ISCO}} \approx 4400\,M_\odot/M$. An inspiral signal will enter the LIGO band at a low frequency cutoff, $f = f_{\mathrm{low}}$ corresponding to a time t_{low}. This template has a duration of $t_0 - t_{\mathrm{low}}$ and is critically sampled at a rate of $2f_{\mathrm{isco}}$.

Way too many citations here.

The time slices for this template consist of the K intervals $(t_K, t_{K-1}], \ldots, (t_2, t_1], (t_1, t_0]$ sampled at frequencies $f_{\mathrm{K}-1}, \ldots, f_1, f_0$ where $f_0 = 2f_{\mathrm{ISCO}}$, $t_0 = t_{\mathrm{ISCO}}$, $f_{K-1} \geqslant 2f_{\mathrm{low}}$, and $t_K \leqslant t_{\mathrm{low}}$.

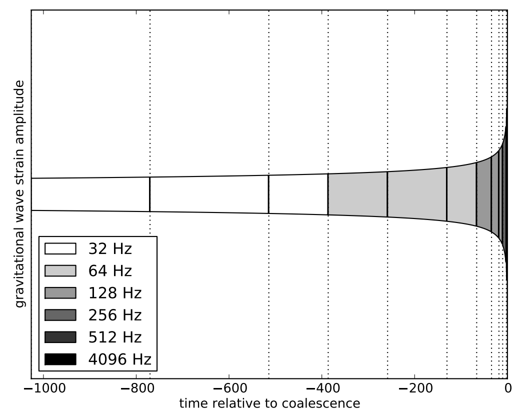
If all of these time slices are implemented using the FFT, then the latency of this filter bank is $\max_j\left[-\left(2(t_j - t_{j-1}) - t_{j-1}\right)\right] = \max_j\left(3t_{j-1} - 2t_j\right)$.

An example time slice design satisfying these constraints for a $1.4 - 1.4\,M_\odot$ is shown in table 1. For this example, the latency for this time slice design is just 125.75 s even if all of the time slices are implemented with the FFT method. This set of time slices will require 619 operations per sample per template, compared with 372 for pure FFT cross-correlation without time slices, or 8.4×10^6 for the FIR filter method without time slices.

2.3. Reducing the number of filters with the singular value decomposition

Our second innovation exploits the fact that the templates in inspiral template banks are, by design, highly correlated. It is possible to greatly reduce the number of matched filters required to achieve a particular minimum match by designing an appropriate set of orthonormal *basis templates.* A purely numerical technique based on the application

Table 1: Example of critically sampled, power-of-2 time slices for a $1.4 - 1.4\,M_\odot$ template extending from $f_{\mathrm{low}} = 10\,\mathrm{Hz}$ to $f_{\mathrm{ISCO}} = 1571\,\mathrm{Hz}$ with a time frequency structure given by (1).



f_k (Hz)	$(t_{k+1}, t_k]$ (s)	Samples
4096	$(-0.25,\ 0]$	1024
512	$(-2.25,\ -0.25]$	1024
256	$(-10.25,\ -2.25]$	2048
128	$(-18.25,\ -10.25]$	1024
128	$(-34.25,\ -18.25]$	2048
128	$(-66.25,\ -34.25]$	4096
64	$(-130.25,\ -66.25]$	4096
64	$(-258.25,\ -130.25]$	8192
64	$(-386.25,\ -258.25]$	8192
32	$(-514.25,\ -386.25]$	4096
32	$(-770.25,\ -514.25]$	8192
32	$(-1026.25,\ -770.25]$	8192

of the singular value decomposition (SVD) to inspiral waveforms is demonstrated by the authors in [20].

One may regard a bank of N discretely sampled templates of length M samples, $h^{\mathrm{W}}(\theta_i; t_j) = [\mathbf{H}]_{ij} = H_{ij}$, as a matrix. The singular value decomposition is an exact factorization that exists for any matrix such that

I'm sweeping the complex nature of the templates under the rug here. Is it OK to regard our packing of the real and imaginary parts of the SVD as an implementation detail? It makes the math a little more concise.

$$H_{ij} = [\mathbf{V}\mathbf{\Sigma}\mathbf{U}]_{ij} = \sum_{k=1}^{N} v_{ik}\sigma_k u_{kj}, \tag{2}$$

where $\mathbf{V}$ and $\mathbf{U}$ are both unitary matrices and $\mathbf{\Sigma}$ is a diagonal matrix. For our purposes, we associate the rows of $\mathbf{U}$ with a minimal set of basis templates, which become the kernels of basis filters. These filters give rise to the orthogonal SNRs, $[\rho^\perp]_k = \rho_k^\perp = \mathbf{U}_k \star x^{\mathrm{W}}$. The rows of $\mathbf{V}\mathbf{\Sigma}$ become reconstruction coefficients that map linear combinations of the orthogonal SNRs from the basis filters back onto SNRs for the original templates of interest: $\rho_i = \sum_k [\mathbf{V}\mathbf{\Sigma}]_{ik}\rho_k^\perp$.

In many applications of the SVD, including ours, the matrix can be well approximated by truncating the summation in equation (2) at $L \ll N$:

$$H'_{ij} = \sum_{k=1}^{L} v_{ik}\sigma_k u_{kj} \tag{3}$$

The cumulative sum of squares of the *singular values*, σ_k, measures the Frobenius norm of the approximation, such that

$$\frac{\|\mathbf{H}'\|}{\|\mathbf{H}\|} = \left(\sum_{k=1}^{L} |\sigma_k|^2\right)^{1/2} \left(\sum_{k=1}^{N} |\sigma_k|^2\right)^{-1/2}. \tag{4}$$

This is also called the SVD tolerance. In our application, it relates to how much SNR is lost by discarding $N - L$ of the basis filters with the lowest singular values.

This result differs from other work that models gravitational-wave chirp signals in approximate ways [21, 22, 23] by starting with an exact representation of the desired template family and producing a rigorous approximation with a tunable accuracy.

This sounds confrontational to me, but these are good citations. Can we tone it down?

2.4. Composite detection statistic and hierarchical detection

Although the SVD allows us to reduce the number of matched filters, this comes at the price of having to perform a matrix multiplication by the reconstruction matrix $\mathbf{V\Sigma}$ at every sample. In some circumstances, this matrix multiplication may be more expensive than applying the orthogonal matched filters.

We should cite [24] here.

Further speedup may be gained in a hierarchical detection scheme. In general, the orthogonal SNRs alone provide some indication of whether any template in the original template bank is likely to have a large SNR. Consider some composite detection statistic that is a scalar function of the orthogonal SNRs, $\Gamma(\rho_1^\perp, \rho_2^\perp, \cdots, \rho_L^\perp)$. Suppose that we can infer the distribution of Γ for a data stream with the signal present or with the signal absent. Then we may use a threshold crossing of Γ to trigger the conditional application of the expensive reconstruction matrix only during the times when a signal is likely to be present.

The composite detection statistic that we employ is a weighted sum of squares, $\Gamma = \sum_{k=1}^{L} w_k (\rho_k^\perp)^2$, with the particular weights

$$w_k = \frac{\sigma_k^2}{\sigma_k^2 + N/A^2}. \tag{5}$$

Here, A is a desired SNR scale that is set by the analyst. As the authors show in [25], this choice of weights has a better receiver operating characteristic for a signal of SNR $= A$ than some other obvious choices, $w_k = \sigma_k^2$ or $w_k = 1$.

We now have a pretty good description of time slices, the SVD, and conditional reconstruction. We still need to tie it all together.

Should I mention `GStreamer` at all?

3. Implementation and Analysis

The detection method described above is much more efficient in terms of floating point operations than the traditional matched filter bank method. However, time slices and conditional reconstruction greatly complicate queueing, synchronizing, and bookkeeping of intermediate signals. A low latency implementation capable of recruiting more than one CPU core would be difficult to achieve within the familiar serial programming framework because of the nontrivial time-delay relationships between samples. Due to these complications, we chose to prototype the search using an open source signal processing environment called `GStreamer`. Primarily used for playing, authoring, or streaming media on `Linux` systems, `GStreamer` is an integral component of the popular `Gnome` desktop.

Citation for `GStreamer`?

It would be good to illustrate the layout of this particular template bank: masses spanned, time slice layout . . .

4. Results

- 1 day of simulated $h(t)$.
- $h(t)$ has power spectrum ~~prescribed for "zero detuning, high power" model in [26]~~ that somewhat resembles initial LIGO noise models
- $h(t)$ generated by passing white, Gaussian noise through a bank of IIR filters
- 1 noninjections run
- 10 injections runs
- injections are distributed uniformly in log distance, uniformly in sky location and binary orientation
- injections are reweighted to be uniformly distributed in volume

Drew: I think this should say the FFT version of LLOID is almost 10 times faster than the conventional FFT method.

Table 2: Operation counts per sample for six different detection methods. The operation counts for LLOID assume a reconstruction duty cycle of 5%. Note that the FIR method with LLOID is almost 10 times faster than the conventional FFT method, despite having substantially lower latency.

operations/sample	latency (s.)	method
3 714 580 480	2.4×10^{-4}	conventional FIR method
49 937	1.8×10^{3}	conventional FFT method
522 381 677	2.4×10^{-4}	FIR method with SVD
25 983	1.8×10^{3}	FFT method with SVD
522 363 923	2.4×10^{-4}	FIR method with LLOID and no time slices
8 229	1.8×10^{3}	FFT method with LLOID and no time slices
1 587 712	2.4×10^{-4}	FIR method with time slices
173 926	2.5×10^{-1}	FFT method with time slices
120 673	2.4×10^{-4}	FIR method with time slices and SVD
74 498	2.5×10^{-1}	FFT method with time slices and SVD
51 285	2.4×10^{-4}	FIR method with LLOID
5 110	2.5×10^{-1}	FFT method with LLOID
2 146	2.5×10^{-1}	same, with cascade topology
1 612	2.5×10^{-1}	same, with cascade topology 2

- injections are 80±20 seconds apart
- there are ≈ 10k injections

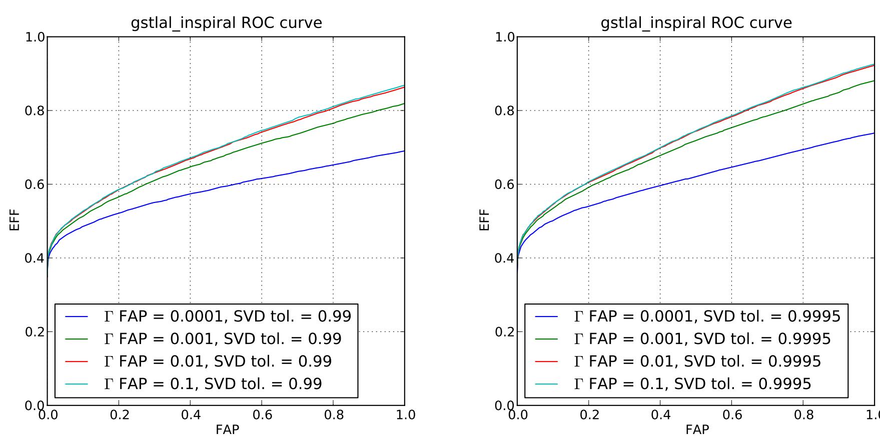


Figure 1: Receiver operating characteristic (ROC) curve of detection efficiency (EFF) versus false alarm probability (FAP).

5. Conclusions

Acknowledgments

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Appendix A. Floating point operation counts

The filter bank can be implemented using finite impulse response (FIR) filters, which are just sliding window dot products. If there are M templates of length n, and the data stream contains N samples, then applying the filter bank requires $2MNn$ operations.

I just yanked this from the methods section. It needs to be made more concise, maybe turned into a table of CPU budgets for various components of LLOID.

More commonly, the matched filters are implemented using the FFT convolution. This entails applying FFTs to blocks of D samples, with $2n \leq D$, each block overlapping the previous one by n samples. There are $N/(D-n)$ such blocks. Modern implementations of the Cooley-Tukey FFT, such as the ubiquitous **fftw**, require about $4N \lg N$ operations to evaluate a DFT of size N [27]. A D sample cross-correlation consists of a forward FFT, an D sample dot product, and an inverse FFT, totaling $8D \lg N + 2D$ operations per block. Per sample, this is $(8 \lg D + 2)/(1 - n/D)$ operations.

This is more commonly known as "overlap-save". We should find someone else's operation count and cite it.

Drew: Why don't we change this to an overlap of m samples so we can see what happens as we increase the overlap to reduce latency.

The FIR filter implementation has the advantage that it has no intrinsic latency, whereas the FFT convolution has at least the latency of the FFT block size $D \geq 2n$. For example, for a $1.4 - 1.4\,M_\odot$ template with duration ~ 1 ks, the FFT convolution has a latency ≥ 2 ks. However, the FIR filter implementation has the disadvantage of much greater overhead per sample than the FFT convolution. For a 1 ks template sampled at 4096 Hz, the FIR implementation requires about about $n/8 \lg 2n = 2.2 \times 10^4$ times more operations per sample than the FFT implementation.

Drew: Should the latency be D-n?

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