# Analyzing Intermediate-Mass Black Hole Triggers Using the Bayesian Coherence Ratio

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***Abstract*—The Bayesian Coherence Ratio (BCR) is a statistic which rejects glitches in LIGO data using the fact that glitches are typically less coherent between detectors than real signals. This statistic was originally used on glitches from O1 LIGO data for low-mass binary-black hole systems. We apply the BCR on intermediate-mass black hole data and determine that, while not quite as strong, the BCR is still valid in rejecting a large percentage of IMBH glitches.**

## I. Introduction

The Bayesian Coherence Ratio (BCR) is a statistic used to distinguish real gravitation-wave (GW) sources from both glitches and pure Gaussian noise [1]. Given $D$ detectors, we write

$$BCR = \frac{\alpha Z^S}{\prod_{i=1}^{D}[\beta Z_i^G + (1-\beta) Z_i^N]}.$$

Here, $Z^S$ denotes the evidence for the signal model, $Z^G$ the evidence for the glitch model in a given detector, and $Z^N$ the evidence for the noise model in a given detector. The $\alpha$ and $\beta$ parameters in this equation are priors for the given models: $\alpha$ is the prior belief in the signal model, $\beta$ is the prior belief in the glitch model, and $1-\beta$ is the prior belief in the noise model. Together, these priors and evidences allow us to separate incoherent glitches from coherent signals. The values $\alpha$ and $\beta$ may be estimated by choosing values which give the largest amount of separation between signal and background distributions.

## II. Background

In using the BCR we need a suitable method to identify background events given LIGO data. This background data is found by performing time-slides between data from multiple detectors, changing the time offset of one detector relative to the other. Additionally, to obtain a sizable amount of signal data, we use software injections to add signal to typical background noise in each detector.

After obtaining enough instances of signal and background data, we run parameter estimation (PE) runs on each selection of data to obtain our signal, noise, and glitch evidences. This can be done with the help of software packages such as bilby [2]. The noise and glitch evidences in each detector come from parameter estimation runs using data from one detector only. The signal evidence comes from a PE run using data in multiple detectors.

Given the data from the PE runs for each piece of signal or background data, we then calculate the BCR for each run, tuning $\alpha$ and $\beta$ to create the greatest amount of separation between the signal and background triggers. Typically, we choose a BCR of 1, or log-BCR of 0 as a cutoff between signal and background distributions, which can be shifted accordingly by using $\alpha$ to re-scale the data. Correspondingly, tweaking $\beta$ is what actually creates the separation between the two distributions.

After the prior weights $\alpha$ and $\beta$ are determined, the BCR can now be used to veto possible triggers whose log-BCR falls below the zero threshold. This allows us to correspondingly decrease the false-alarm rate (FAR) of any trigger whose BCR passes the cutoff, depending on the percentage of glitches in the background distribution which have log-BCR $< 0$.

## III. Previous Uses for Low Mass Triggers

The BCR was originally used in [1] to analyze triggers from the O1 PyCBC pipeline. With this method, 98% of background triggers were found to have a log-BCR below zero. Here the background triggers were selected to be uniform in inverse false-alarm-rate, and all of the background triggers and software injections had total masses estimated to be less than 100 solar masses. The weights that were found to best separate the signal and background distributions were $\alpha = 10^{-6}, \beta = 10^{-4}$.

## IV. Transitioning to IMBH Triggers

While the BCR as shown works very well in separating low-mass signal and background triggers, in transitioning to intermediate black hole (IMBH) sources (with total mass over 100 solar masses), we expect background triggers to have a much larger degree of coherence between detectors. This is due to the fact that higher-mass events have a much shorter signal duration, so it is much more likely for a glitch to be coherent between detectors in the smaller timeframe. This larger degree of coherence would make it much harder to separate the signal and background distributions, and thus the BCR could prove to be less useful in vetoing glitches and decreasing FAR for real events.

However, even if a 98% improvement is out of reach for IMBH triggers, something on the order of an 80-90 percent veto for background triggers could provide a significant improvement in FAR for real events.

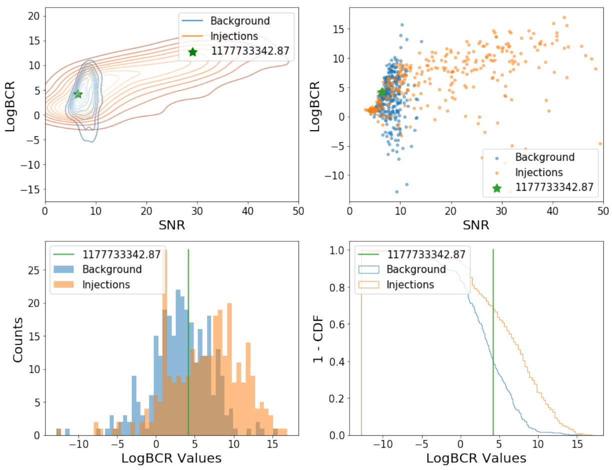


Fig. 1. IMBH Weighted BCR vs SNR distributions with $\alpha = 1, \beta = 1$

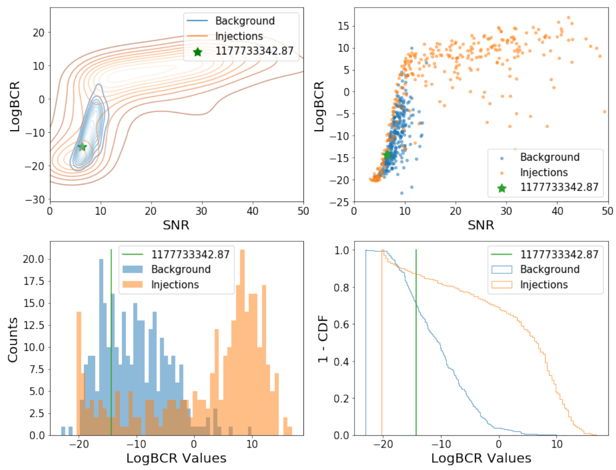


Fig. 2. IMBH Weighted BCR vs SNR distributions with $\alpha = 10^{-8}, \beta = 10^{-4}$

## V. Methods

All of our parameter estimation runs are done using the dynesty (dynamic nested sampling) package in python as a part of the bilby parameter estimation package [2]. Data segments are all four seconds in length, and we use the IMRPhenomPv2 waveform for all of our analyses.

All of our IMBH triggers used in the analysis come from the Coherent Wave-Burst (CWB) pipeline, which ranks triggers by a re-weighted signal-to-noise ratio statistic $\rho$ [3]. We take the top 300 IMBH background triggers in $\rho$ for our background timeslides. Additionally, we perform 300 software injections with total mass between 100 and 400 solar masses. These injections are uniformly distributed in distance with signal-to-noise ratios (SNRs) ranging from 0 to 50.

Finally, we run parameter estimation runs using data from the 170502 IMBH trigger. This trigger was the most significant observed in the O1 + O2 IMBH search. Its FAR was estimated to be 0.34, not significant enough to call a real event, and checks identified a correlation between this trigger and an optical lever laser glitch. However, if its BCR fell above the background threshold, its FAR could be decreased accordingly.

## VI. Results

For our preliminary results, when analyzing BCR values with setting $\alpha = 1, \beta = 1$ (also known as the BCI) in Figure 1, we find very little separation between the signal and background distributions. In contrast, varying $\alpha$ and $\beta$ leads to a much better separation between signal and background. Here, with results for $\alpha = 10^{-8}, \beta = 10^{-4}$ shown in Figure 2, we see that most of our background events are below the zero threshold and most of our signal events are above the threshold, especially above SNRs of 10. Specifically, we find that 96% of background triggers are below the cutoff while 91% of software injections above SNRs of 10 are above the cutoff. Additionally, from the data we see that the 170502 IMBH trigger has network SNR too low for any valid veto to be determined by the BCR.

When looking at the metric as an extra veto used to rule out possible glitches, we see promise in the large separation between signal and background distributions with the final weights. From the original distributions in background triggers in $\rho$, we see in Figures 3 and 4 that applying the BCR as a veto takes away a very large portion of the existing background events and would significantly lower FAR in real events. However as we approach lower values of SNR, we see that the BCR is doing nothing to separate the distributions. This is the one main difference we see between intermediate-mass black hole events and low-mass black hole events from [1]. This is likely due to the larger degree of coherence allowed in shorter-duration glitches. Even though our signals are still more coherent at low-SNRs, the margin is too slim for the BCR to yield any useful result. As we approach larger SNRs, however, we see that the distributions separate much more, especially when compared with the results for $\alpha = 1, \beta = 1$. As most mergers cannot be observed at SNRs below 10, we see that the BCR is still performs well in rejecting IMBH glitches. We suggest that, at the very least, the BCI (BCR with $\alpha = 1, \beta = 1$) statistic shown in some PE software packages and other analyses should be replaced with the BCR using better choices of weights.

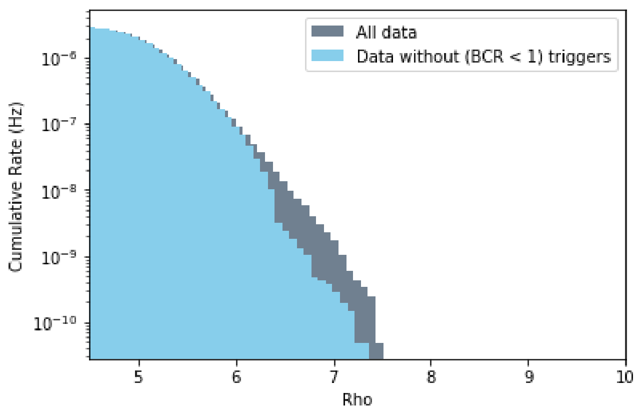


Fig. 3. Cumulative background distributions in $\rho$ with and without PE runs with $BCR < 1$, logarithmic scale.

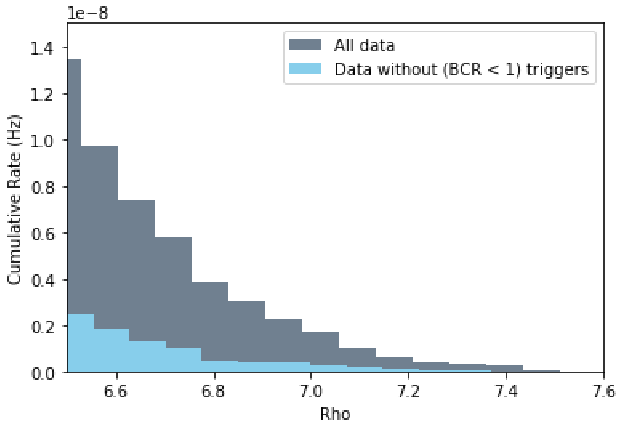


Fig. 4. Cumulative background distributions in $\rho$ with and without PE runs with $BCR < 1$, linear scale.

## VII. Items for Further Analysis

In the next steps towards using the BCR in the future, it would be useful to finalize the 'correct' choices in weights for $\alpha$ and $\beta$. As mentioned in [1], this could be done with sampling a very large number of glitches and software injections, with masses ranging in both the low and intermediate mass ranges, and separating the distributions as before. However, due to the differences in $\alpha$ values found, it's possible that the weights vary between low and intermediate mass events, which could be taken into account.

Additionally, the weights can be determined as the priors they are defined to be, instead taking the approach of finding the general odds of finding a signal in Gaussian noise and a glitch in Gaussian noise. It's also possible that this would still cause $\alpha$ and $\beta$ to vary from low to intermediate mass ranges.

Aside from the weights, we can look into using the BCR on other pipeline data. It's likely that new pipelines have a more polished system for finding signals and glitches, and thus it would be good to see how well the BCR does compared to previous runs.

## References

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