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HONS 497
Honors Thesis

Parameterization of BayesWave for Analysis of Gravitational Waves Caused by Inspiraling Black Holes
LIGO-P1600111

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ABSTRACT

Gravitational waves are ripples in the fabric of spacetime caused by large gravitational events. LIGO was built to detect gravitational wave signals. By analyzing these signals, it is possible to gain a greater understanding of gravitational waves and their sources, which include binary stars, supernovas, and black holes. Algorithms such as BayesWave are designed to analyze signals detected by LIGO. However, BayesWave remains unoptimized in many areas. By examining BayesWave's analysis of an injected gravitational wave signal while systematically varying several adjustable parameters, this research further optimized BayesWave for the analysis of gravitational waves caused by inspiraling black holes.

I. INTRODUCTION

Physicists have been interested in gravitational waves ever since Albert Einstein predicted them as a consequence of general relativity in 1916, although for decades they were assumed to be either too weak to detect or nonexistent. Despite the general skepticism concerning gravitational waves, physicist Joseph Weber attempted to detect them in the 1960s. Although they did not succeed in detecting gravitational waves, their efforts did revive scientific interest in them. As a result of this revived interest, scientists sought to build gravitational wave detectors and, on September 24, 2015, the first direct detection of gravitational waves took place.

Gravitational waves are ripples in spacetime caused by gravitational events. They propagate outwards from their source at the speed of light, and they momentarily stretch space as they pass through. Although gravitational waves are generated by all gravitational events, they are extremely faint. A gravitational wave with maximum expected strength passing through Earth changes its radius by only 10^{-14}m. Considering the extreme faintness of gravitational waves, an extraordinarily sensitive instrument must be used to detect them. LIGO[1], the Laser Interferometer Gravitational Wave Observatory, was built for this purpose. As the name suggests, LIGO is a large laser interferometer. There are currently two LIGO locations, in Livingston, Louisiana and Hanford, Washington.

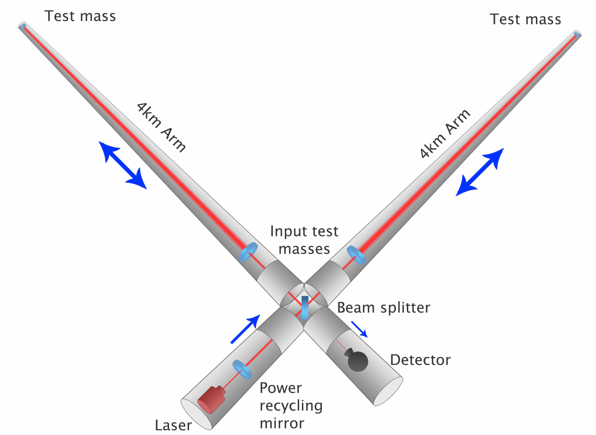

Figure 1: Simplified diagram of LIGO [Chris North, Cardiff University]

The LIGO detectors are interferometers with 4km arms. Each interferometer is set up so the laser light in the branches interferes destructively, creating an interference pattern. When a gravitational wave passes through the interferometers, the path traveled by the laser light changes by an amount that would be imperceptible through most methods of measurement: in this case, by a distance smaller than the radius of an atomic nucleus. Even small changes in the length of the interferometer's arms cause changes in the interference pattern. These signals contain information about the gravitational waves that caused them. Interference patterns that closely resemble theoretical gravitational wave signals, such as those resembling the theoretical signal caused by inspiraling binary black holes, are flagged for further analysis.

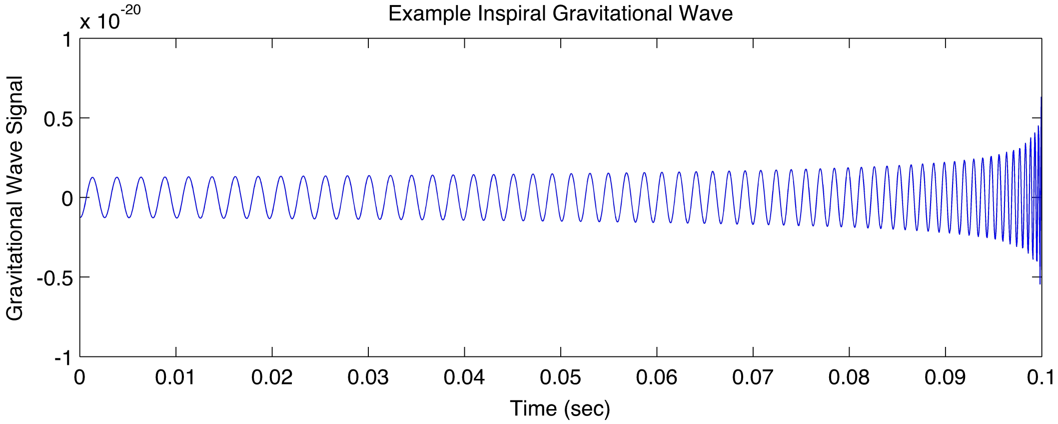

Figure 2: Theoretical binary black hole inspiral signal [A. Stuver/LIGO]

Once this data has been gathered, it must be properly analyzed. The LIGO Scientific Collaboration (LSC) uses existing models for the gravitational waves generated by various sources, for instance by two inspiraling black holes[2]. However, these theoretical models do not take the vibrational noise that LIGO detects into account. Although LIGO uses sophisticated noise-isolating technology to cancel out most of the vibrations around it, the extreme sensitivity of the detector combined with the sheer amount of vibration sources make background noise inevitable[3]. As such, in order to effectively analyze gravitational wave data collected by LIGO, the background noise must first be subtracted out of the gravitational waveform as completely as possible. In addition, glitches – transitory, non-Gaussian disturbances in the data that do not fit the same model as background noise – must be accounted for, or they could interfere with the detection and analysis of faint gravitational waves.

BayesWave is one algorithm used to extract gravitational wave signals[4]. It uses a series of wavelets, in combination with Bayesian model selection methods that vary the number of wavelets used in order to prevent overfitting, to model wave functions. It also uses several pre-specified priors to predict glitch amplitude and signal amplitude, and BayesWave uses a model based on the expected shape of the noise data to subtract out much of the background noise. BayesWave uses the noise function and the prior parameters to construct a posterior distribution function, which is used to extract the waveform. When properly parameterized, BayesWave's extracted waveforms can be nearly identical to the original gravitational wave signal[5]. These extracted waveforms provide valuable information about gravitational waves and about the sources that generated them.

II. METHODS

The BayesWave algorithm's results depend heavily on the values of the prior parameters, including the peak prior, glitch prior, and signal amplitude prior. While BayesWave has undergone tests before[6], due in part to the large amount of time and processing power needed, there has been relatively little investigation into exactly how these priors change BayesWave's accuracy and effectiveness.

This research investigates the effectiveness of BayesWave when using parameters between the values of 2 and 10, specifically in the case of analyzing the gravitational wave signal caused by inspiraling black holes. In order to test the effectiveness of various parameterizations of BayesWave, we used synthetic binary black hole inspiral signals injected into Gaussian noise that has been filtered to match the scale and frequency of early Advanced LIGO data. Because the signal was injected into simulated LIGO data, this provided a good test of how effective BayesWave was at accounting for noise.

Additionally, because the injected signal is a known quantity, it was possible to directly compare the injected and extracted waveforms through both graphical and numerical means. A particularly useful method of quantifying the similarity of the two waveforms is

$$M = \frac{(\bar{h}|h)}{\sqrt{(\bar{h}|\bar{h})(h|h)}} \ , \tag{1}$$

where h represents the injected signal, $\bar{h}$ represents the extracted signal, and $h|\bar{h}$ represents the inner product of the two signals[7]. The result of this equation, M, will have a value $-1 \leq M \leq 1$, where 1 represents a situation where the extracted signal is identical to the injected signal. In general, the closer that M is to 1, the better the extracted signal is.

By using scripts to automate the creation of injected signals in synthetic LIGO data and to pass parameterization choices on to BayesWave, it was possible to run multiple trials of various parameterizations of BayesWave[8]. Specifically, we varied the amplitude prior, which conveys information about the amplitude of glitches in the data; and we varied the signal prior, which conveys information about the expected signal-to-noise ratio of the injected signal. By running repeated extractions with varying values of the amplitude prior and signal prior, and by visually and mathematically examining the accuracy of the extracted signal, it was possible to examine the relative effectiveness of BayesWave when running under several values of the signal prior parameter and amplitude prior parameter.

III. RESULTS

A. Amplitude, Signal Priors = 2

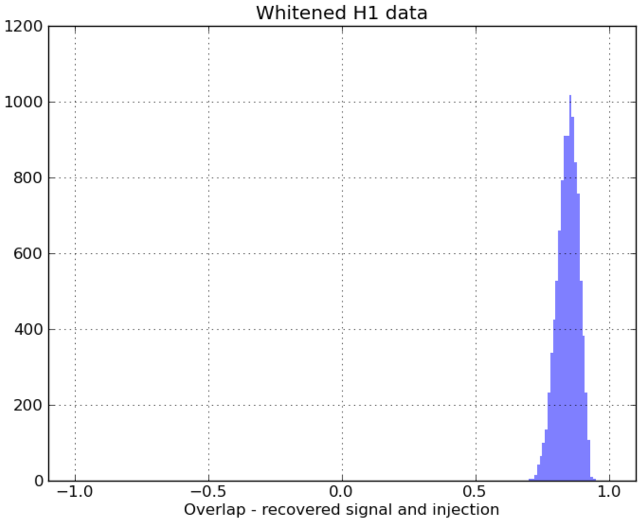

Figure 3: Overlap between injected and extracted signals

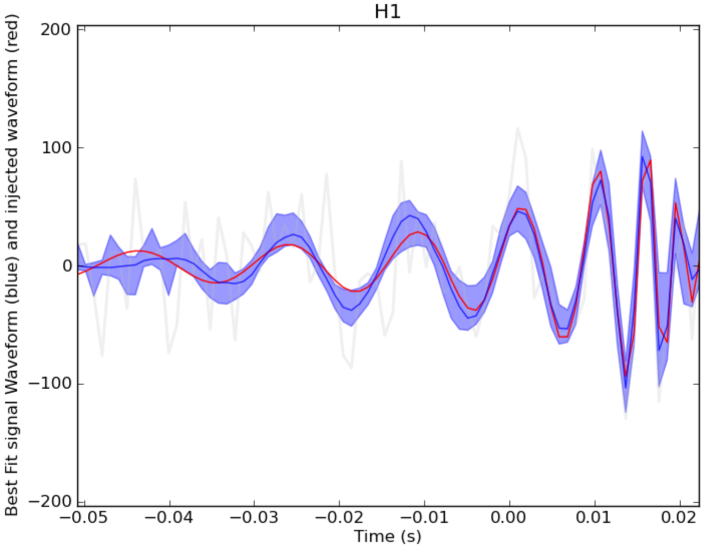

Figure 4: Close-up of the injected and extracted signals. The blue line is the extracted signal, the red line is the injected signal.

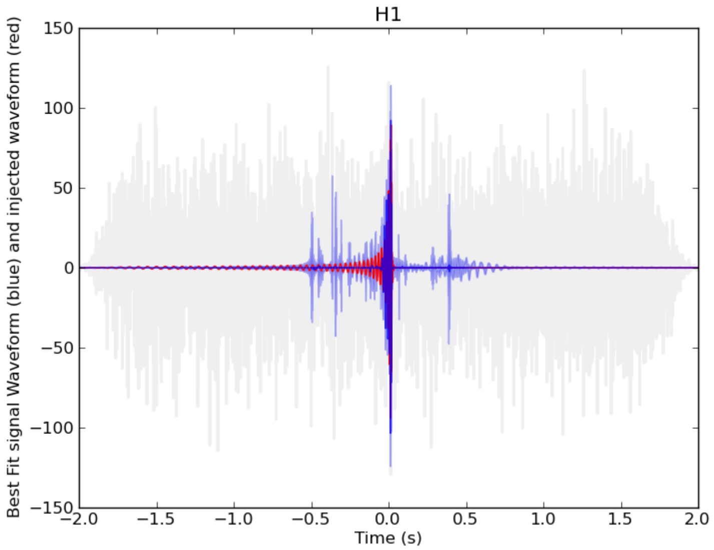

Figure 5: Overview of the injected and extracted signals. The blue line is the extracted signal, the red line is the injected signal.

The results from the runs conducted with signal and amplitude priors of 2 are promising. Figure 3 shows a histogram of the overlap between the injected and extracted signal, which peaks at M=0.825. Considering that the maximum M-value possible is M=1, this is a good result. Figures 4 and 5 provide further support for the effectiveness of this parameterization. Figure 4 in particular shows how closely the extracted signal follows the injected signal, even in the presence of a great deal of interference from the greyed-out background noise. Figure 5 gives a broader view of the parameterization, showing the injected and extracted signals, along with the noise they were injected into, through a period of four seconds. There are some obvious flaws in the extracted signal – it maintains a relatively large magnitude after the injected signal has faded, for one – but the approximate shapes of the two signal correspond closely. Although the red injected signal is difficult to see where it overlaps with the blue extracted signal, when examined closely it is possible to tell that two signals are nearly identical at the central peak.

B. Amplitude, Signal Priors = 4

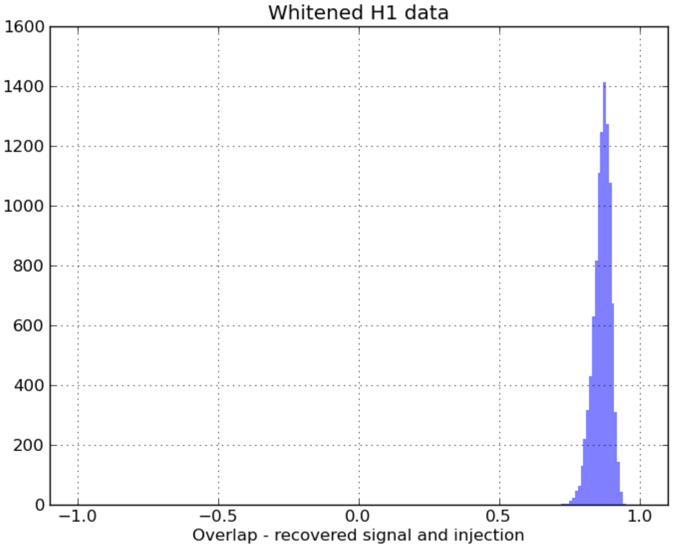

Figure 6: Overlap between the injected and extracted signals

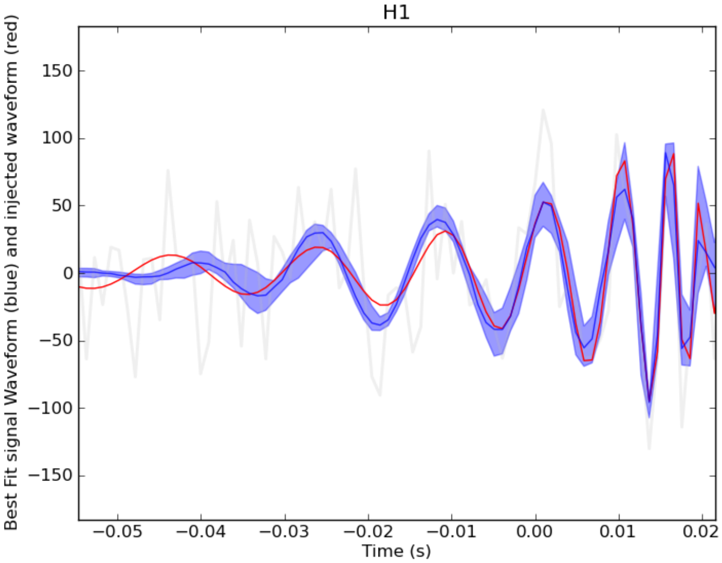

Figure 7: Close-up of a section of the injected (red) and extracted (blue) signals

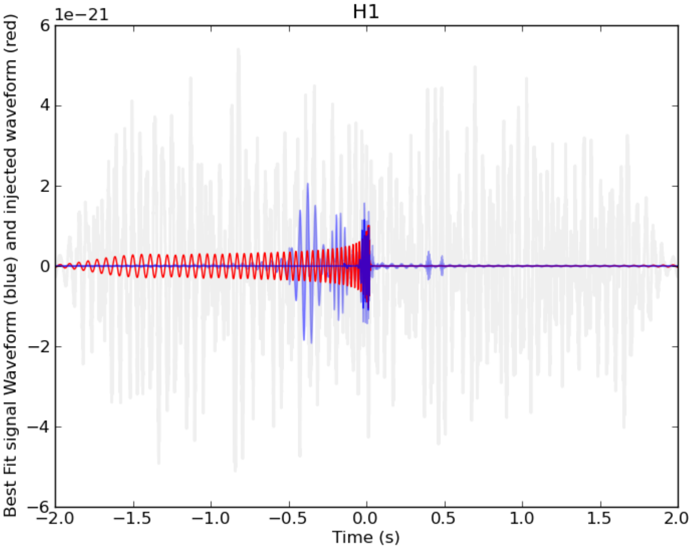

Figure 8: Overview of the injected (red) and extracted (blue) signals

The results for signal and amplitude parameters of 4 are very similar to those with signal and amplitude priors of 2. Here, Figure 6 shows the overlap of the injected and extracted signals. Once again, the overlap is good but not perfect, with an M=0.865. The two other completed jobs had similar M-values. Figure 7 demonstrates that the injected and extracted signals do correspond quite closely, while Figure 8 gives a broader picture of the signals. Once again, the extracted signal follows the injected signal very well where the injected signal has a relatively large amplitude. We also see the same lagging effect evident previously, however. The extracted signal is initially of lesser amplitude than the injected signal, and it continues with relatively large amplitude as the injected signal fades. There are also spikes in the extracted signal that are not present in the injected signal, probably in response to BayesWave attempting to model some of the noise in addition to the signal.

IV. DISCUSSION

Our results through this research show that parameterizing the signal and amplitude priors in the range of 2-8 is promising. The parameterization at 4 was particularly good, with its M-value of 0.865. Although this parameterization is not perfect, BayesWave successfully extracted a signal that was recognizably similar to the injected signal in the parameterizations of 2 and 4. This range of parameterization requires further investigation. Due to time constraints and the large amount of processing power BayesWave requires, out investigation was limited to a relatively small number of runs, each of which took over 24 hours to complete. Although the parameterization of 4 appears the most promising, further investigation is needed to verify it. It would also be useful to investigate how BayesWave's results change when parameters are changed independently of each other, rather than as a group. Additionally, the cluster prior was being reviewed during the time of this research and was not included in our investigation. Once it is returned to use, it's effect on BayesWave's extraction of binary black hole signals should also be analyzed.

Although further research is required, this project did demonstrate that BayesWave is an effective at extracting binary black hole signals while parameterized in the range of 2-8. This is a valuable addition to LIGO's knowledge base because of the difficulty of analyzing and extracting gravitational wave signals, particularly when they have a small signal-to-noise ratio. So far, the only confirmed gravitational wave measured by LIGO has been an extremely strong signal from inspiraling binary black holes, but we hope and expect to detect other gravitational waves in the near future. Many of these signals will likely be much fainter, less readily recognizable as gravitational wave signals, and more difficult to extract data from. It will be increasingly important to have parameterized algorithms that are confirmed to be able to extract fainter signals from among glitches and detector noise.

V. BIBLIOGRAPHY

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