Measuring Impacts of Glitch Removal on Gravitational Wave Parameter Estimation

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(Dated: November 6, 2020)

No scientific endeavor ever runs flawlessly. There are always malfunctions and interference that cause the data to be less than perfect. In the case of gravitational wave data, one of the defects often found in the signals are noise transients, called glitches. These glitches are often difficult to model due to their non-Gaussian nature. It is not currently routine practice to remove them, although sometimes glitch subtraction must be done when the glitch strongly interferes with the signal. Each glitch is unique. The process of glitch subtraction is time consuming and has not yet been tested and documented in a systematic way. We hope to add to the documentation on the effects of glitch removal on parameter estimation by running parameter estimation on a data set of simulated signals with glitches injected at varying distances from the signal. We will then remove the glitch from the data and run parameter estimation on the clean waveform. This will allow us to study how the distance between the glitch and the signal plays a role in the accuracy of the parameter estimation. While we discovered that the presence of the glitch has a recognizable affect on recovering the parameters, we have yet to draw conclusions on how the distance of the glitch from the signal affects these results. We anticipate that there may be a distance at which the glitch subtraction has negligible affect on estimating parameters.

I. INTRODUCTION TO GLITCH MITIGATION

The detection of gravitational waves, which requires extremely high detector sensitivity, is made even more difficult by high-amplitude, abrupt noise transients, which we call "glitches"[1]. Glitches can be registered as false-positives of gravitational wave signals from merging binary black holes (BBH) and binary neutron stars (BNS), or the rarer case of a black hole-neutron star binary (BHNS). Both black holes and binary neutron stars are the final stages in the lives of massive stars, although it requires a higher mass to form a black hole. Figure 1 gives an example of the signal we hope to see during binary coalescence, with no glitches present. In this specific case, the frequency of the signal gradually increases from less than 50Hz to more than 100Hz over the course of 30 seconds. The shape of this signal is what we commonly call a chirp. The signal track is clearly visible in both the Hanford and Livingston data [2].

We currently do not know why these glitches occur, although they are thought to be the result of environmental disturbances or instrumental malfunctions. Multiple problems arise from the presence of glitches: the detection of signals becomes less significant, and search sensitivity is degraded [3]. Visually, we can see how the glitch obscures a gravitational wave signal in figure 2. This figure also shows how a model of the glitch compares to the strain data [2]. In the top panel of figure 2 the glitch appears as a spike in frequency, with a normalized amplitude of about 6, higher than the signal's normalized amplitude which appears to be about 4 or 5. The model of the glitch, as seen in the bottom frame of figure 2, is essential to this project. [4].

We believe removing glitches allows us to make more accurate parameter estimation (PE), although whether or not this assumption is true has not yet been systematically tested. The removal of glitches is not a trivial problem. The simplest way to subtract the corrupted data would be to "zero it out", which can be done using a "gate" that injects zeros in place of the unwanted data. This method is not reliable, as it can cause leakage of excess power to nearby data, proving to be more harmful to the results than the initial glitch [3].

The method of masking and inpainting [3] proves to be a better option for glitch removal, however it is not the one we used in our study. This procedure is more complicated than the prior and involves several more steps, the math of which is too extensive for this report. An example of the results of this method can be seen in figure 3. We chose to focus on glitch subtraction using the BayesWave program that models the glitch's wave function and removes the model from the original strain data.

The goal of this project was to subtract glitches in a systematic way that allows us to draw conclusions on the effect glitch subtraction has on PE. While we did not have time to complete all our initial goals in the 10-week duration of our project, we found interesting results that have spurred continued research on the subject. Specifically, this paper will address the impact of the glitch on recovering signal parameters such as chirp mass and mass ratio. As BayesWave glitch subtraction is a computationally intense process that requires many hours to produce an output, it would save valuable time to ignore the glitch altogether. In our study, the glitch can only be ignored, however, if its presence has negligible affect on PE. In our results, we found drastically different parameter estimations with and without a glitch present, although we are wary of the accuracy of our PE because neither results align with our expectations.

II. METHODS FOR GENERATING A DATA SET

To simplify the data set, one signal, paired with Gaussian noise, and one glitch, was used. When building the data set we began with choosing a glitch. The chosen glitch is from event S190413ac because this glitch has a relatively high energy, and therefor we predicted it would have a large negative impact on PE. We did not want to conduct an experiment only to find the glitch we chose was not loud enough to produce insightful results.

Next we generated Gaussian noise using the functions pycbc.psd and pycbc.noise in python. Lastly, we created a signal. The choice between using a real signal and a simulated signal was an easy decision because only a simulated signal allows the true parameters, such as individual masses, to be known and controlled. It was essential that we be able to determine exactly how impactful the presence of the glitch was on obtaining accurate PE. The signal needed to be as long as the glitch in the time domain so the signal was zero-padded (a process which places a string of zeroes before the waveform to add length). To do this we simply found the difference in length (in the time domain) between the glitch and the signal and added enough zeros to fill this difference to the end of the signal waveform. The model IMRPhenomD was chosen to generate the waveform due to its signal tapering capability. This was essential, as moving abruptly from zeros to the signal's amplitude caused horizontal, over-saturated lines to appear in the spectrogram (q-scan). Masses of $m_1 = 20M_{sun}$, and $m_2 = 25M_{sun}$ were chosen because these are "common" mass values. Initially we chose identical masses of 10 solar masses, however this value was too low to be considered a common mass and assigning both bodies identical masses was unrealistic.

III. APPROACH TO TESTING IMPACT OF THE GLITCH

Before the proposed project could be carried out, some time was spent learning how to operate BayesWave. After successfully running a test job on BayesWave we were ready to work with our own data set. We began by creating our "control" data set, with which we could compare our glitch-corrupted data. The control data consisted of only Gaussian noise and the injected signal. We created this data for both the Livingston and Hanford detectors, finding that the signal appeared more strongly in the Livingston detector. We then ran parameter estimation on this data set using the program Bilby.

Next we created a "corrupted" data set by injecting the glitch into the data for the Livingston detector. We chose the Livingston detector over the Hanford detector because the glitch was significantly louder than the signal in the Hanford detector. We feared the glitch would completely overpower the Hanford signal and make it impossible for Bilby to detect the signal at all. We then ran Bilby PE on the corrupted data.

Finally, we ran the corrupted data through BW to subtract the glitch and create our "cleaned" data set. We intended to run PE on the cleaned data but we ran out of time. We then wanted to compare PE from the cleaned data to PE from both the control data and the corrupted data to determine which it more closely resembled. This would have allowed us to draw initial conclusions about the effectiveness of BW glitch subtraction. If BW is not as effective as we hope, it may be wise to abandon this glitch subtraction method in favor of a more effective method.

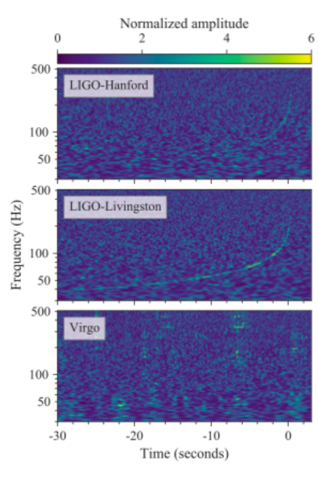

FIG. 1. This figure is adopted from [2] and shows three graphs of the detection of a signal without any glitches present from event GW170817 [2]. The LIGO-Livingston observatory detected the signal most strongly. This is a good example of glitch-free data.

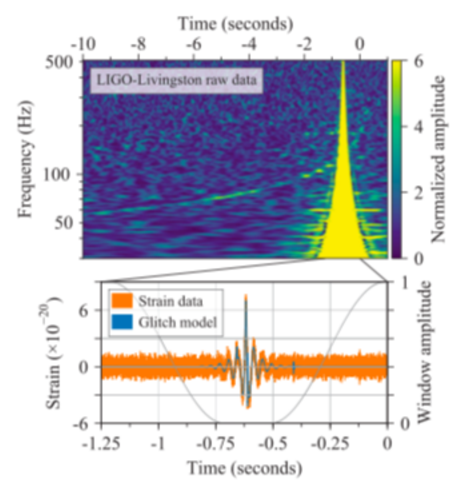

FIG. 2. The detection of the glitch in the LIGO data above with the model of the glitch below for event GW170817 [2]. In the top image we see the glitch as a bright transient which obscures a portion of the signal. Below we have the raw data plotted in orange and the model of the glitch in blue. It is this model that will then be subtracted from the strain data.

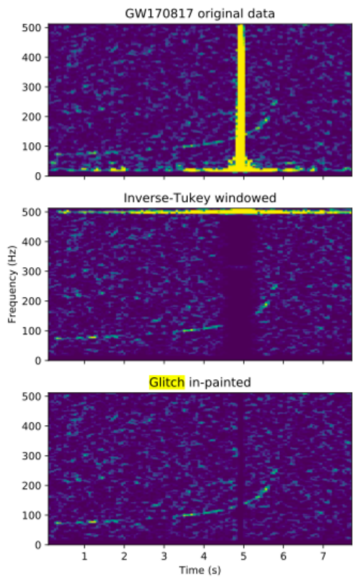

FIG. 3. This image is adopted from [3]. It is an example of masking and inpainting for kilonova (binary neutron star collision) event GW170817 [3]. Upper panel shows the whitened spectrogram of the raw data where a glitch is clearly visible. The middle panel shows the bad data gated away using an inverse-Tukey window. The bottom panel shows the inpainted result.

IV. RESULTS

A. Current Findings

The Bilby parameter estimation run produces posteriors of various parameters. We decided to focus on two parameters that are extremely important to recover: mass ratio and chirp mass. The mass ratio is simply the ratio m_1/m_2. For this data set we should recover a chirp mass of $20/25 = 0.8$, however that is not what we found. For the data set without the glitch injected Bilby produced a flat posterior distribution with a median value of 0.732 as can be seen in figure 4. The expected distribution shape is that of a Gaussian, with a clear peak, indicating a clear "best" value was determined. With this distribution that was not the case, and the median value does not give convincing evidence that the mass ratio was accurately recovered, even without a glitch present. The median chirp mass value for the frame with the glitch present was even farther from the true value: 0.527. In this case we can see the data is dramatically skewed to the left. This posterior exhibits behavior that is known as "railing against the prior." The prior is a set of conditions set before running Bilby. One of these pre-selected values is a minimum mass ratio, which was set at 0.5 for this data set. It is likely that the posterior would have produced an even lower estimate for the mass ratio, had a lower minimum limit been assigned.

The second parameter we investigated is chirp mass, which is given by the equation:

$$M_{chirp} = \frac{(m_1 * m_2)^{3/5}}{(m_1 + m_2)^{1/5}}$$

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From this equation we calculated an actual chirp mass of 19.44 M_{sun}. Both of the posterior distributions for chirp mass, however, revealed to be inconsistent with this known value. As can be seen in figure 5, the posterior for the glitch-free data is skewed dramatically to the left and appears to be once again railing against the prior. The real chirp mass sits at the far right of the graph and does not overlap with the posterior at all. This is a strong indication that something went wrong when running Bilby parameter estimation, although we do not yet clearly know what the source of the problem is. In the top panel of figure 5 we see the posterior of the data with the glitch. The presence of the glitch clearly has a large impact on the shape of the posterior distribution, resulting in two large peaks with little data anywhere else.

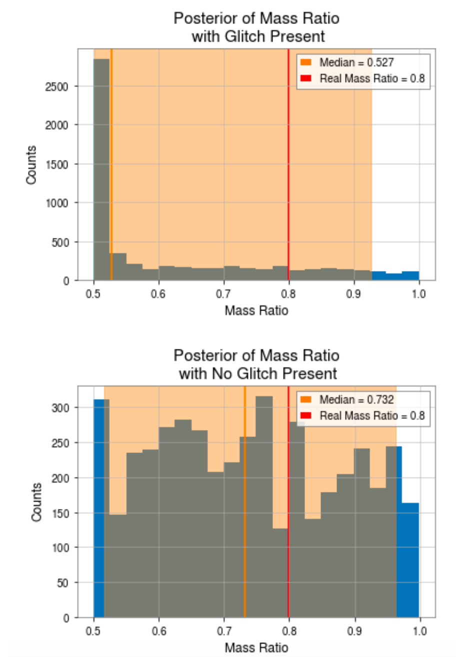

FIG. 4. Posterior plots for mass ratio parameter. The median of the posteriors is marked with an orange vertical line and the value is displayed in the legend. The real mass ratio value is marked with a red vertical line and the value is also displayed in the legend. The top panel is the posterior for our simulated data with an injected glitch. The bottom panel is the posterior from the same data only without the injected glitch.

B. Future Work

To continue this project we plan to conduct a more rigorous study of both the effectiveness of BayesWave glitch

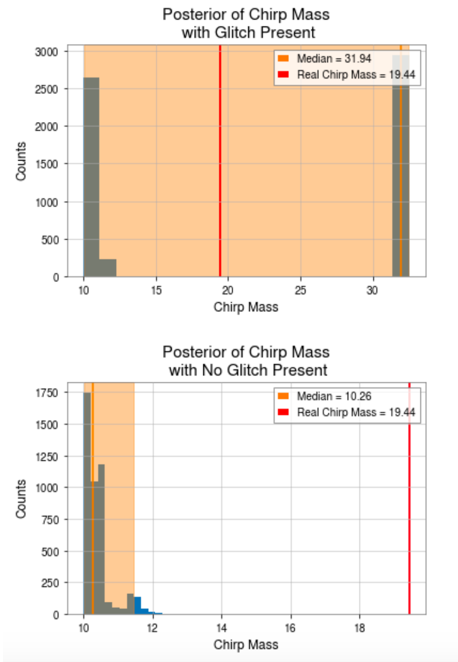

FIG. 5. Posterior plots for chirp mass parameter. The median of the posteriors is marked with an orange vertical line and the value is displayed in the legend. The real chirp mass value is marked with a red vertical line and the value is also displayed in the legend. The top panel is the posterior for our simulated data with an injected glitch. The bottom panel is the posterior from the same data only without the injected glitch.

subtraction in general, and specifically of the effect of glitch subtraction on parameter estimation. Before expanding the study we will first locate the source of our problems with Bilby which must be resolved before we can move forward. Once we have successfully run Bilby on the data presented in this report, we will expand to a larger data set. When creating the new data we plan to choose a new glitch, perhaps a blip glitch as these are one of the most common glitches and pose potential problems for BayesWave due to their close resemblance to signal chirps. Currently, we plan to use the same simulated signal, although this may be altered if the signal is too weak for Bilby to accurately determine the parameters. The main question we will focus on answering is the one we aimed to answer in this study: is there a cut-off distance at which the glitch is far enough away from the signal that its presence has no negative impact on recovering accurate parameters?

We will make a data set of 20 different frames, with the glitch at 20 different times in relation to the signal. In answering this question, we also hope to gain a more comprehensive understanding of how well BayesWave glitch removal successfully subtracts the glitch from the data. Bilby PE will be run on all 20 frames and their posteriors will be compared to a clean frame Bilby posterior, just as was done in this study. BayesWave glitch subtraction will then be run on any frames where the presence of the glitch has a significant impact on PE. The BayesWave cleaned frames can then be run through Bilby and their posteriors can be compared with the original glitch-free posterior and the glitch-present posterior to determine which it more closely resembles.

With these results we hope to be able to draw meaningful conclusions on how the proximity of the glitch to the signal impacts a necessity for glitch subtraction. BayesWave glitch subtraction is a computationally expensive, time consuming process which does not lend itself to the speedy results desired for quick data analysis. If we can predetermine instances when glitch subtraction is unnecessary we could save valuable time by leaving out this step.

V. ACKNOWLEDGEMENTS

I would like to thank my mentors Jonah Kanner and Alan Weinstein for creating this project and offering guidance along the way. Alan Weinstein provided me with an education on gravitational wave physics that improved my overall understanding of the research conducted by LIGO and informed me on the significance of this specific project in the larger picture of gravitational wave astronomy. Jonah Kanner offered guidance and support throughout, helping me to make sense of my findings and teaching me valuable skills on how to effectively communicate my research. I would also like to acknowledge Derek Davis who spent hours with me debugging code and Colm Talbot who aided me in understanding and running Bilby. I would like to thank Tyson Littenberg for his assistance with BayesWave and for providing overall project guidance. Lastly, I would like to acknowledge the NSF, specifically the NSF REU program, Caltech SURF, and LIGO for providing me with the opportunity to conduct this research and with the funds to do so.

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