Mitigating the effects of instrumental artifacts on source localizations

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Abstract

Instrumental artifacts which materialize as glitches in strain data can overlap with gravitational wave detections and significantly impair the accuracy of sky localizations. To fix this problem, we are proposing a method to precisely zero out the data and analytically reproduce the signal-to-noise ratio (SNR) of the correct signal which will translate to a sky localization likely to be more accurate than previously designed methods to address glitches. Additionally, we include our proposal for the development of a tool to detect glitches in the data and automatically apply the SNR correction to real gravitational wave events. We discuss the context which determines our starting point, our approach to developing this tool, and how we will test its effectiveness.

1 INTRODUCTION

Detection of gravitational waves requires extreme sensitivity to changes in length on the order of 10^{-18} m [2]. The level of strain sensitivity, characterized in Figure 1 as a function of frequency, renders LIGO detectors susceptible to noise transients (or glitches) in the strain data. Often, the cause of these glitches are difficult to determine. They can be the result of either external environmental or internal instrumental interactions that alter the actual strain. Glitches are more likely to overlap with gravitational wave (GW) events that occur for a longer period, such as binary neutron star (BNS) events. As detection of GW events from BNS mergers become increasingly frequent [4], we expect to see more instances of noise transients overlapping with GW signals as seen in the case of BNS merger GW170817 [3]. This is problematic for many reasons, especially because noise transients diminish the accuracy of rapid sky localization and parameter estimates of the source. In order to gain useful and accurate astrophysical information from a GW event, it is important these glitches be fixed in a way that minimizes bias in localization measurements. There are multiple approaches one can use to try and address this. For GW170817, the effects of the

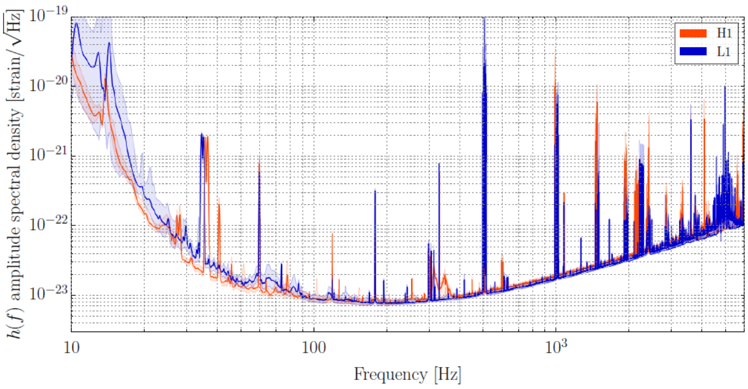

Figure 1: Average measured strain sensitivity as a function of frequency for LIGO-Hanford (H1) in red and LIGO-Livingston (L1) in blue. Spectral features are due to mechanical and instrumental resonances. Replicated from [1].

noise transient were mitigated by applying a window function to remove it. The glitch was then reconstructed with

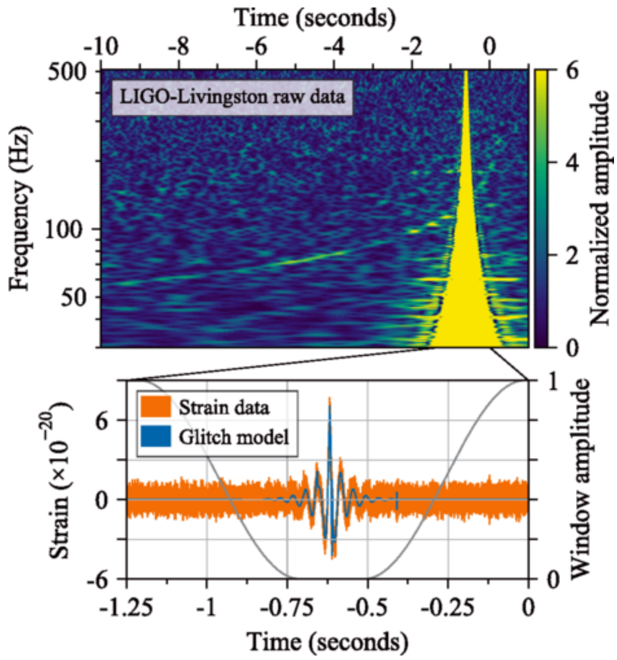

Figure 2: *Top panel*: Time-frequency plot of LIGO Livingston data for GW170817 with the glitch present. *Bottom panel*: Strain data of the glitch, with a grey window function used to zero it out. The reproduced model of the glitch is shown with the blue curve. Replicated from [3].

a model that could be subtracted from the data, as shown in Figure 2. This method was ad hoc in nature, different approaches are necessary to find a generalized solution for all GW events.

An alternative to window functions is inpainting [8], where the affected data are zeroed out and some data around the hole is replaced by values obtained from analytical calculations, shown in Figure 3. Effectively, it minimizes the amount of data that is zeroed and preserves more of the signal.

NNETFIX is a method which attempts to approximate the data in the zeroed out region [5]. NNETFIX utilizes neural networks and machine learning algorithms to estimate the portion of data lost to the glitch and approximate a reconstructed timeseries in its place. This improves the accuracy of sky localization as opposed to only removing the glitch with a window function.

In this proposal, we introduce a solution to noise transients that will combine inpainting with an analytical solution to replace missing data that is likely to improve upon accuracy of previous methods. Like NNETFIX, this will be applicable universally to GW events unlike the method used to mitigate noise in GW170817. In this proposal we will outline our goals for the project, discuss how this tool will be developed and tested, and provide a brief overview of the project schedule.

2 OBJECTIVES

Our ultimate project goal is to write a tool that is able to reproduce the correct SNR timeseries without the glitch. When a glitch appears in the strain data, the SNR increases as a result. If we can correct the SNR by the right amount, we can then investigate how to translate this result to an accurate sky localization in BAYESTAR [7].

We will be able to evaluate the effectiveness of this tool by analyzing its accuracy of its sky localization capabilities for ≈1000 simulated GW events. Once we are able to use the tool for simulated events, we will then apply it to a real event.

We can compare the accuracy of this method to only inpainting the hole, only applying a window function, and NNETFIX. This result will take the form of a plot, comparing the sky localization abilities of each method vs the expectation. Ultimately, we will be able to determine which method is the best for accurate and widely applicable to remove glitches in strain data.

A secondary goal is to create a tool that can identify glitches automatically in real GW events. Along with this, a way to automatically apply the tool we create to correct the SNR and sky localization will make it easier to use for future glitch removal from GW signals.

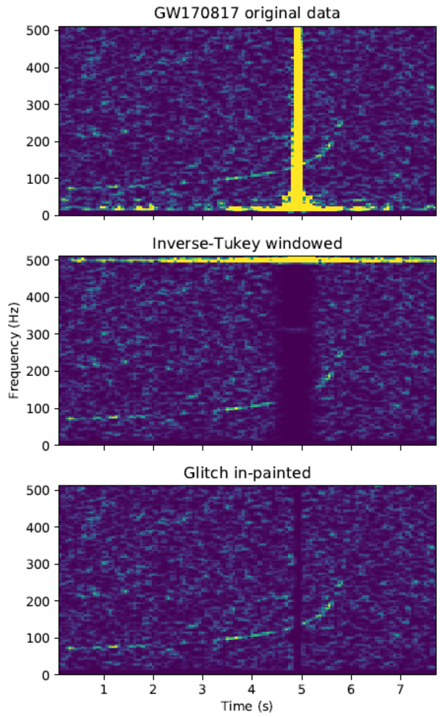

Figure 3: *Top panel*: Time-frequency plot of LIGO Livingston data for GW170817 with the glitch present. *Middle panel*: Strain data with the glitched removed by a window function. Note the leakage from spectral at the top of the graph. *Bottom panel*: LIGO Livingston data with the glitch inpainted. Replicated from [8].

3 APPROACH

There are six main steps to complete in order to carry out our objectives. Steps 1-3 will be sufficient to complete the primary project goals, and steps 4-6 will be worth completing if time permits. These steps are as follows:

- The most important and time-consuming step will be to design a tool that will be able to inpaint a hole in strain data, recover the SNR, and correct the SNR. For inpainting the hole, we compute an overlap with the inpainted data [8]:

$$\tilde{z_w} = h^\dagger C^{-1} F d \tag{1}$$

  Where h_i and d_i are the components of the template waveform, C is the covariance matrix of the noise, and F is the inpainting filter. We renormalize the overlap due to the presence of the hole and can compute this to fill in the hole and only zero out the bad segments of data:

$$z_w = \left(\frac{h^\dagger C^{-1} h}{h^\dagger C^{-1} F h} \right)^{1/2} \tilde{z_w} \tag{2}$$

  We can then compare this method with recovering the SNR of the signal without inpainting [6]:

$$\rho^2(t) = \frac{4}{\langle h|h \rangle} \int_0^\infty \frac{\tilde{s}(f)\tilde{h}^*(f)}{S_n(f)} e^{2\pi i f t} df \tag{3}$$

  Where ρ is the SNR, h is the template waveform, d the data, and $S_n(f)$ is the estimated one-sided power spectral density of the noise around the time of the event.

- After the tool is written, we will determine how to use our corrected SNR with the BAYESTAR skymap tool to get a sky localization.

- We will show this sky localization can accurately represent the location of one simulated source. During this step, we will go back and tweak the work done in the previous steps to successfully accomplish this goal.

- When we have one sky localization, we will apply the tool to ≈1000 simulated signals to ensure that it is reliable and precise and that the success of our previous step is reproducible.
- If time permits, we will also develop a tool that can detect glitches in the data automatically to determine where the corrected SNR method needs to be applied.
- Finally, we write a script to use this process automatically for real GW events and produce a tool that can be easily used to correct real noise transients as soon as they occur.

4 PROJECT SCHEDULE

The tentative timeline for the 10-week project can be split in two halves, with the first five weeks spent training and the second five weeks implementing the steps outlined in the approach. During the training period:

- First weeks will be spent training on how to inpaint the data around holes for removed glitches.
- After inpainting, there will be training on how to recover the SNR of GW signals.
- Training in using and developing sky mapping algorithms such as BAYESTAR will also be covered.

After the first half, the training will be directly applied to developing a new tool to recover data from noise transients. The last couple weeks will be spent working on the final steps of the approach, conveying the results, and creating a final report.

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