SURF Second Interim Project Report

Examining Change Points in LIGO Hanford Data over Observing Run 4 to Improve Detector Performance

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August 3, 2024

DCC: T2400227
California Institute of Technology
LIGO Hanford Observatory
National Science Foundation

Contents

1 Narrow Spectral Artifacts

1.1 Background and Motivation

Previously, we have provided a formal definition of the usage and motivation of the cost-function and discrepancy to analyze change-point methods in incoming noise. As defined previously, my project's aim is to utilize python to detect change points in detected LIGO noise. This is motivated to determine the behavior and persistence of particular combs over the duration of several dates over the O4a run.

Identical methods for using cost-functions in the form of the sum of least square has remained identical. However, an additional discrepancy has since been changed for simpler plotting and data detection. Our purpose was to keep the window-sliding technique introduced in the change-point detection methods for signal processing, but the discrepancy curve was then changed to be plotted between 0 and 1, which allows for an easier threshold to be established to the discrepancy data. As such, our initial discrepancy plot was depicted as:

$$D(y_{a,t}, y_{t,b}) = c(y_{a,b}) - c(y_{a,t}) - c(y_{t,b}) \tag{1}$$

However, this discrepancy function, when applied over a comb, outputted various line heights over certain frequencies, which became difficult for an appropriate threshold to be established. Hence, the discrepancy function has been modified to:

$$D(y_{a,t}, y_{t,b}) = 1 - \frac{(c(y_{a,t}) + c(y_{t,b}))}{c(y_{a,b})} \tag{2}$$

Which made the development of a threshold possible for each frequency.

Furthermore, previous methods of incorporating a provided penalty function to a criterion function (see Interim Report 1) has been considered for the purpose of isolating segmentations of said change-points. The penalty function has been defined as:

$$Pen_{l0}(\tau) := \beta|\tau| \tag{3}$$

However, the smoothing parameter (β) in (3) is assumed with an established data model and a known variance. Given how the analyzed combs do not have a previously determined variance amongst change-points, it was necessary to disregard establishing the penalty function to the criterion, and consider alternative methods.

One such alternative method is to establish a discrepancy curve (defined above) for plotting, in which the peak prominence package from SciPy may isolate and distinguish between slope-points and peak-points in the discrepancy array for each comb range. Following this, a threshold may be introduced to then distinguish the exact moments of said change-points from the line-height graphs. This will then be able to be compared to the respective dates on which said change points occur.

1.2 Ongoing Progress

Following the failure of properly implementing the smoothing parameter to the penalty function, this hence rendered the method of the criterion function inefficient for our particular purposes. As such, the immediate next steps were choosing a particular comb range for O4a line heights. The past chosen frequencies were 24.4 hertz and 24.5 hertz, respectively. This has since changed to 6.977 hertz, with frequency combs varying with the following equation:

$$f_n = f_0 + n * \delta f \tag{4}$$

Where f_n refers to the tooth frequency, f_0 is the offset (from 0 hertz), n is an integer, and δf is the a spacing. The 6.977 hertz frequency was implemented with $n = 26$, and then stored in an array for each n multiplication of 6.977 hertz.

This was then plotted, with the line height of each frequency over each date in O4a depicted in the below figure. Visual change points are immediately noticeable around November 2023, which was noted and compared to the subsequent graphs. As accomplished before for the 24.4 and 24.5 hertz frequencies, the line height for each integer multiple of the 6.977 hertz frequency was then inputted into an implemented cost function in python, and was then stored into a new array.

The discrepancy curve was then calculated from the cost functions of the comb range, and then plotted with an established window size. The labeled plot below depicts this calculation. It is important to note the change points in the discrepancy curve visually align with the change points in the line height graph. Both are plotted over the same dates as well.

From the discrepancy curve, ongoing methods are to attempt to establish a new arranged array with the peak prominence, and then establish a threshold for the prominence array. Doing so would isolate the change points of the original line heights of the combs.

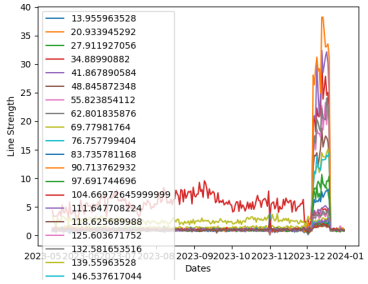

Figure 1: Line Height vs. Dates for 6.977 Hertz Comb

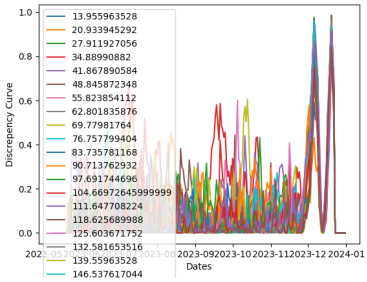

Figure 2: Discrepancy for 6.977 Hertz Comb

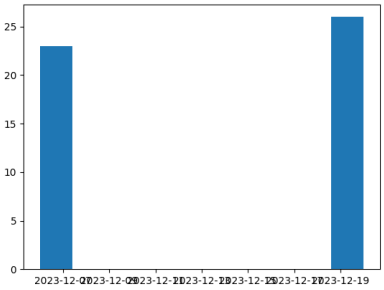

Figure 3: Number of Change Points over Respective Dates

1.3 Challenges and Potential Solutions

One of the underlying challenges of the alternative method is the development of a proper threshold after the arrangement of peak prominence. Determining this threshold must be based nearly entirely on visual interpretation of the change points in the shown line height curve. As such, this manual input may prove to be problematic due to inaccurate visual approximations.

Another potential challenge may be incorporated already automated techniques to unknown combs and lines over the O4 run duration. The tested computation has been sampled specifically on combs with an already known number of change points. As such, this may lead to uncertain data analysis.

2 Lockloss Tagging and Plugin Development

2.1 Background and Motivation

Lockloss occurs when the suspended mirrors deviate heavily from their nominal, causing them to lose control and disrupting data analysis. Lockloss events themselves are monitored via the Locklost tool plugins, which determine correlating factors to surrounding phenomena which could explain the reason for losing lock. For example, seismic activity may impact mirror deviation.

One phenomena occurring prior to lockloss are glitches. Glitches may be defined as an unknown oscillation in the channel monitoring the output to the lowest suspended mass of the ETMX suspension. There is not an apparent cause for such glitches, and they do not appear to correlate to any any other correlating tag. As such, the establishment of a detection window for these glitches of 1 second to 100 milliseconds prior to the lockloss event was necessary.

Furthermore, because a variety of channels may detect a lockloss at differing times from each other, it was also necessary to develop a plugin which would tag for the input mode cleener (IMC) losing lock at either the same time as other main channels, or 50 milliseconds after. Another instance of channel refinement may also be to establish saturation thresholds for any ASC channels.

2.2 Ongoing Progress

As established in interim report 1, there were complicating factors in the development of an appropriate window-range for the glitch detection. As such, there was a refinement of this window. With strict monitoring from the 1 second to 100 millisecond range prior to lockloss, the threshold was then implemented to check for glitches both above and below the zero-axis. As such, this will not only determine a window prior to lockloss, but furthermore introduce a detection of said glitch with an appropriate threshold. This was promptly incorporated within a refinement plugin of the Locklost tool.

Following this, an additional measure was needed to check whether certain IMC channels detect a lockloss at the same time as the IFO. In order to determine this particular change, code was developed to compare the refined GPS times of both events, and tag the IMC with a "SAME" tag if it loses lock at the same detected GPS time of the main IFO, or within 50 milliseconds. This was then promptly tested on all of O4, which led to no detection. However, the tag was triggered over the O3 run, which indicates the tag works correctly. This also indicates the channels lose lock at separate times, especially over the entirety of O4.

The next step was monitoring the entirety of tag counts over the O4 run, including glitch detection and "SAME". This was included in a summary plot, shown below. Furthermore, their counts over the O4 run were also recorded and plotted in a histogram, shown in the figure below.

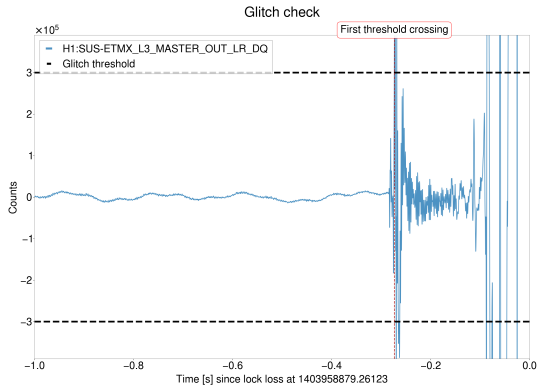

Figure 4: Glitch Detection for event 1403958880

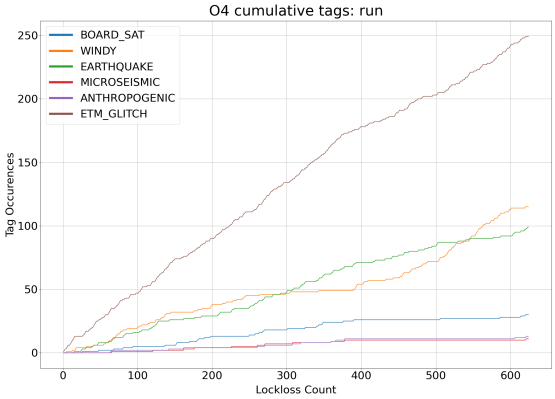

Figure 5: Cumulative Tags over O4 run

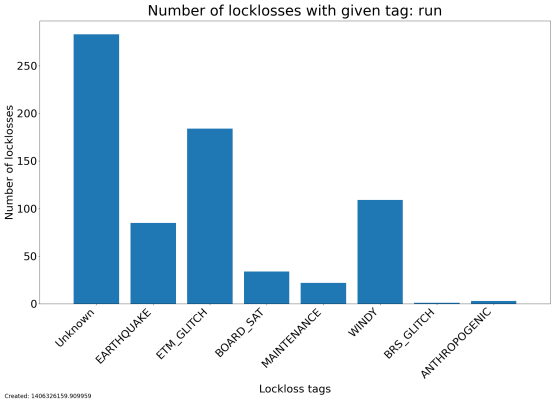

Figure 6: Total Lockloss Tags over O4

2.3 Challenges and Potential Solutions

The development of both an appropriate window and threshold was the biggest challenge for ETM glitch detection. After the development of the standard deviation route, there are still certain cases for the glitch tag to appear when there are no prevalent glitches. In such cases, the threshold is detecting the lockloss event itself. As such, further refinement of the glitch detection method is required, which may require an additional plugin.

Additional investigation into the consistency of the "SAME" tag for IMC channels may be required, due to the lack of detection in the O4 runs. While this may not necessarily be a consistent challenge, the tagging of only particular lockloss events is a next development into analyzing the conditions of these lockloss events.