# Investigations of Binary Neutron Star Range Oscillations at LIGO Livingston

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## 1. Introduction

Gravitational waves were first predicted by Albert Einstein in the early 1900s [1]. Sometimes thought of as "ripples in spacetime", gravitational waves are produced by extreme astrophysical events, like the merging of two black holes or neutron stars. It was not until recently that the first observation of a gravitational wave was made. On September 14, 2015, the Laser Interferometer Gravitational-Wave Observatory (LIGO) facilities in Livingston, Louisiana (LLO) and Hanford, Washington (LHO) observed a merger of two stellar mass black holes [2], which produced measurable gravitational waves.

Gravitational waves are difficult to detect because they are incredibly weak. The gravitational wave amplitude, often referred to as the gravitational wave strain (GW), can be on the order of $10^{-21}\,\mathrm{Hz}^{-1/2}$ at 30 Hz [3]. Due to their elusive nature, detection requires extreme sensitivity. Both LIGO facilities operate as modified Michelson interferometers in order to achieve the sensitivity required to detect gravitational waves. Some of these modifications include increased arm lengths (four kilometers), optical cavities, and filter cavities, all of which allow us to reach the precision required to measure space-time fluctuations due to gravitational waves. With such large facilities and cutting-edge precision, the potential for noise is seemingly insurmountable.

Detector characterization is the primary group and process responsible for understanding how noise can impact the interferometers. In general, detector characterization is the process by which noise sources are monitored, identified, and addressed. This includes studies of LIGO data quality to identify and mitigate noise sources to improve detector sensitivity [4]. There are hundreds of sensors, including accelerometers, microphones, temperature sensors, and seismometers, placed throughout the detector to help track potential noise sources. One of the ways that detector sensitivity is tracked is via the binary neutron star (BNS) range. The BNS range represents the distance at which a gravitational wave signal from the inspiral of two neutron stars of 1.4 stellar masses with an SNR of 8 can be detected [5].

Since the beginning of the fourth observing run, the BNS range at LLO has had frequent oscillatory behavior with periods of roughly 30 minutes. Oscillations are also observed in many auxiliary channels [6]. The direct coupling of this noise has not yet been identified and that is the main objective of this project. This is important to address, as it significantly affects the range and sensitivity with which we can measure gravitational events. During these oscillations, the BNS range can vary 5-15 megaparsecs in this 30 minute window [4]. These oscillations do not occur consistently, sometimes for part of a day or a whole day, usually disappearing from weeks to months at a time. These oscillations affect the sensitivity of the gravitational wave strain data primarily from 30 to 50 Hz. Due to the wide variety of potential noise sources and auxiliary channels that behave similarly, identifying the channels of these oscillations is difficult.

These oscillations have been appearing for over a year, and many tools have been used to try and understand this behavior. Regression algorithms that have been used in the past in various detector characterization studies include Least Absolute Shrinkage and Selection Operator (LASSO) and Ridge regression [7]. These are tools that help model and determine couplings between sensors. This has been used across a wide range of channels already; however, the results have been inconclusive. Cross-correlation is a time-lag analysis technique that has not yet been tried and may be able to filter out a majority of sensors that are not meaningful.

## 2. Methods

### *2.1. Band-Limited Root Mean Square Plots (BLRMS)*

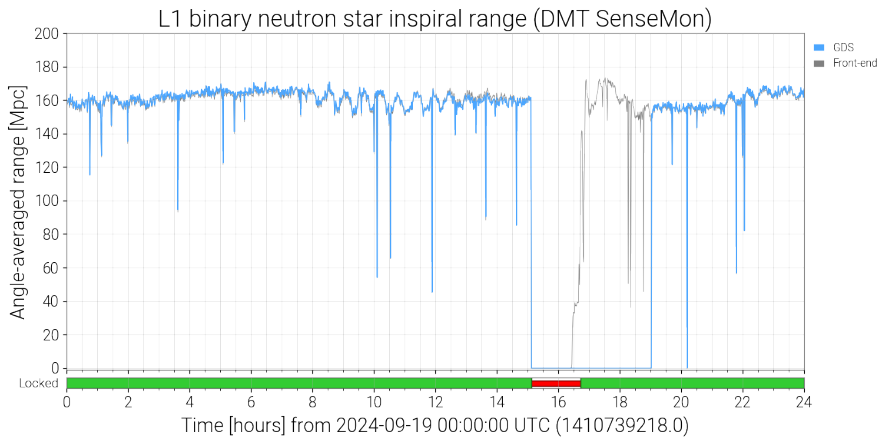
Band-limited root-mean-square (BLRMS) plots are used to study signals within a certain frequency range. Since the oscillatory behavior we were observing in the BNS range was strongest in the 30-50 Hz range, this reduced the amount of data we had to comb through. To begin our search for the source of the noise, we had to see the physical behavior of the auxiliary channels.

A BLRMS was taken of both the gravitational wave strain data and of an individual auxiliary channel. The GW data and the auxiliary channel were then superimposed, which allowed us to visually compare the behavior of the two. Auxiliary channels that had any oscillatory behavior were noted, though auxiliary channels that mimicked the GW data were given special attention. Using these, we can identify possible sensor groupings and locations that are experiencing this noise.

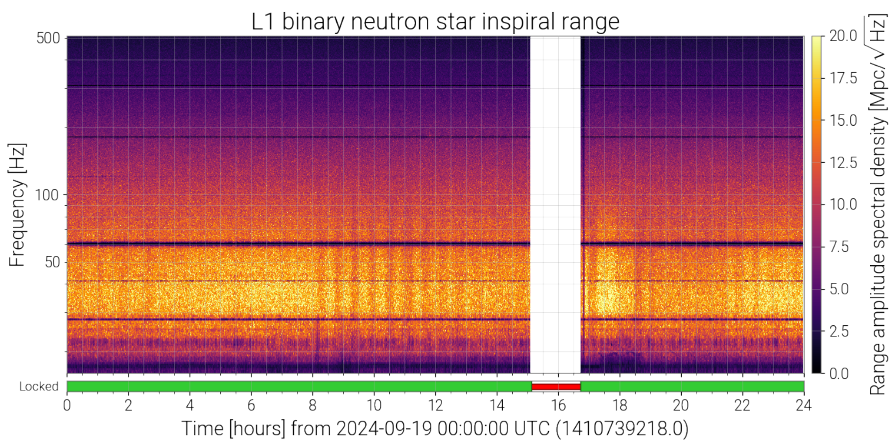
The types of auxiliary channels that had shown oscillatory behavior in the past were the first to be checked. This includes accelerometers, seismometers, temperature sensors, and relative humidity sensors. The accelerometers were observing oscillations in the 30-50 Hz, though the low frequency regime was previously unexplored.

### *2.2. Spectrograms*

Spectrograms are plots that describe how frequency behaves as a function of time. Using spectrograms, we can observe if the frequency changes over a certain period. Looking at Figure 1, which is a spectrogram of the BNS range, we can observe some vertical




(a) top: Visualization of the BNS range on September 19th 2024. 30 minute oscillations are visible from roughly 8 UTC to 13:30 UTC on this day.




(b) bottom: Time-frequency spectrogram where the color represents the amplitude spectral density of the BNS range. During the oscillations, we can see ”stripes” corresponding to changes in noise from 30 Hz to 50 Hz.

Figure 1

lines ranging from 30 to 50 Hz. This indicates some noise is concentrated there with a period of 30 minutes. Spectrograms were then created on auxiliary channels to check if they were observing similar behavior.

The BNS range was observing the noise in the 30-50 Hz range most strongly, however, low frequency noise was unexplored. Low frequencies have the potential to modulate into higher frequencies, or upconvert. This behavior has been observed and noted before with other noise sources separate from this one, but the possibility was still there. Spectrograms displayed the sensors' behavior across a wide range of frequencies, making them an irreplaceable tool.

### *2.3. Cross-Correlation (Time-Lag Analysis)*

Cross-correlation is a data analysis technique that measures how similar two signals are to each other at different time lags [8]. In our case, our two signals are the gravitational wave strain and the auxiliary channel time series data. Time series are essentially measurements taken at fixed intervals. Cross-correlation slides the time series against each other to determine when they are most similar. A lag is the the time delay that a time series is set at when comparing the two, and can be positive or negative. A correlation value is generated along with the lag.

Our cross-correlation routine was written in Python and ran the correlation across the whole time span where the oscillations take place. This worked; however, the time series for both was not always stationary. Stationarity for a time series means that many of the characteristics of a signal are constant in time. This means that the amplitude, mean, and variance do not change for the duration of the signal. For long observing windows, making the approximation that the signals were stationary did not hold strongly. Stationarity is an integral part in signal analysis and is a necessity for cross-correlation [8].

To combat the non-stationarity of our signals, we implemented windowing. Windowing is where we break the observing window into chunks and then run the correlation for each chunk. The correlation values and lags were collected; then the mean and standard deviation were calculated across all windows. This gave us more context on what our values meant and how precise they were.

A negative time-lag, or a preceding auxiliary channel, is more meaningful to us because it may be an initial driver of the noise in the GW strain data that we see. If it drags, that means it may couple with another source of noise or witnesses the noise that contributes to the oscillations we see in the gravitational wave data. If a lag is positive, it means that the signal is "starting" or drags after the signal being tested against. This possibly indicates that the channel is observing the reactions to the noise rather than observing the source itself.

Several days throughout the fourth observing run were analyzed through the time lags. A collection of auxiliary channels, primarily in the End-X station, were cross-correlated against the GW strain. Their mean time lag, mean correlation value, and associated standard deviations were recorded. This large table was filtered by keeping five channels with negative mean lags and highest mean correlation with the standard deviation of the lag being 25 percent of the window duration, which was 30 minutes. A high standard deviation indicates that the lag value per window has significant scattering. Determining whether the channel precedes or lags the noise source is more uncertain with higher standard deviation. Channels that were observed consistently across multiple days were followed up on with additional analysis.

## 3. Progress and Preliminary Results

### *3.1. Project Progress*

The project initially started by combing through the O4a and O4b data and selecting several days that experience the oscillatory behavior. I settled with three days; August 24th, 2023, April 30th, 2024, and September 19th, 2024. These three days roughly span a year worth of time, and where this behavior was most prominent with some padding to give a baseline of the BNS range before or after the oscillations.

Using GWpy [9], a Python-based package used for GW analysis, I pulled the gravitational wave strain data and auxiliary channel data, in this case accelerometers [4] to begin with, for the same time period within that day. I then created band-limited root mean square plots (BLRMS) to get the data into a form that would make the two signals more easily comparable. BLRMS gives us the magnitude of the data, which is a time series, and also allows us to see if noise is appearing in a particular frequency range. This comparison was made to help identify specific auxiliary channels that mimicked or behaved in a similar manner to the gravitational wave strain. Although channels that mimicked the GW data were subjected to more scrutiny, any auxiliary channel that had periodic behavior at any of the frequencies was noted. Temperature sensors were also checked, but due to the sensors only being sampled at 16 Hz, an ordinary RMS was taken. Temperature sensors showed some significant oscillatory behavior that matched the strain data very closely. Most of these auxiliary channels that were studied were in the End-X station, as we think this is where the source of the noise originates. Some notable channels include an accelerometer `L1:PEM-EX_ACC_EBAY_FLOOR_Z_DQ`, a temperature sensor `L0:FMC-EX_VEA_302B_TEMP`, and a seismometer `L1:ISI-ETMX_ST2_BLND_X_GS13_CUR_IN1_DQ`. An example comparison is shown in Figure 2.

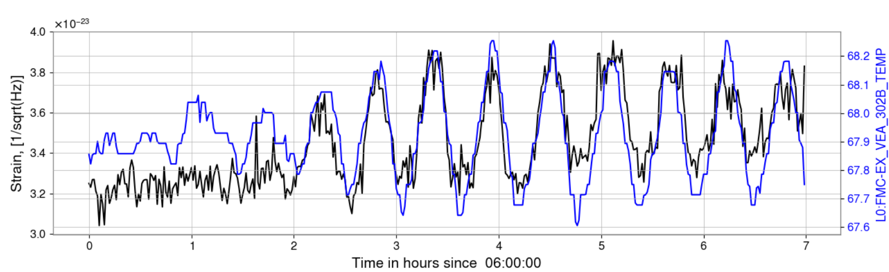



Figure 2: Comparison between a 30-50 Hz BLRMS of the strain data with an end-X temperature sensor.

We computed BLRMS on each auxiliary channel in the 30-50 Hz range, and/or 0.10-0.25 Hz. Low frequency noise was unexplored at the start of this project, but became important to study because it could modulate into the high-frequency range and show up in the strain data [7]. To investigate this, we checked a large list of seismometers at all stations in the low frequency range, as they are well calibrated for low frequencies.

The reasoning for why we wanted to check the low frequency range was that there was potential for low frequency coupling. It is possible for low frequencies to upconvert into high frequency noise and we wanted to rule this out. The seismometers did not show much in the way of oscillations at either frequency range.

In a previous report, we mentioned phase randomization to create a distribution to give some context to the correlation and lag values. We decided to instead break up the time series into chunks; "windowing", and running the correlation between the GW strain data and the auxiliary channels. The reasoning behind this is to try and mitigate any noise spikes that our clipping mechanisms are missing or struggle to handle. Additionally, if there is some sort of period change that we are not observing, this windowing give additional weight to the channels that follow that period change more closely. This windowing is computationally more expensive, but we have found it to provide more robust results since we are taking the mean of the correlation and lags between all windows and also calculating their standard deviation to get a sense of how varied the lags are. Once this program was created, we began expanding the number of days under study.

The cross-correlation script was ran on 23 separate days throughout O4. There were two intervals; December 13-14, 2023 and September 18-20, 2024 that were of particular interest, as the oscillation amplitude was greater. For each day, the top five auxiliary channels that had the highest mean correlation, negative lag, lag standard deviation that was below a 25 percent threshold from the window duration was picked from the data set. Each set was then compiled with the other days' data. With these in hand, we could observe channels that had consistent negative-lag behavior.

### *3.2. Preliminary Results and Future Steps*

Several auxiliary channels were observed to have high correlation with negative lags across multiple days, as seen in Figure 3. For example, `L0:FMC-EX_AHU_FAN1_DISCH_TEMP` and `L0:FMC-EX_AHU_FAN2_DISCH_TEMP` was seen on nine days out of twenty-three. The fact that there are multiple channels that consistently exhibit this behavior is promising. The correlation values and negative lags agree with the temperature sensors having BLRMS that most closely mimicked the GW data.

Future steps would be to perform some follow-up on these auxiliary channels and widening our net to the End-Y and corner station. While early investigations suggested that the source of the noise was at the End-X station, we have not completely ruled out the source being at other stations. Many of the channels that are observing the oscillations are in physical proximity to each other, possibly indicating a source. We speculate that an HVAC fan may be a culprit, but we will not know for certain until physical tests are performed. There is a chance that the oscillations could be a result from the electronics themselves, such as a periodic shift in voltage. This is not unprecedented, so future steps will involve checking these avenues as well. The source of these oscillations is rather evasive, so we must do a a comprehensive comb through the whole facility to make sure that we do not miss something important.

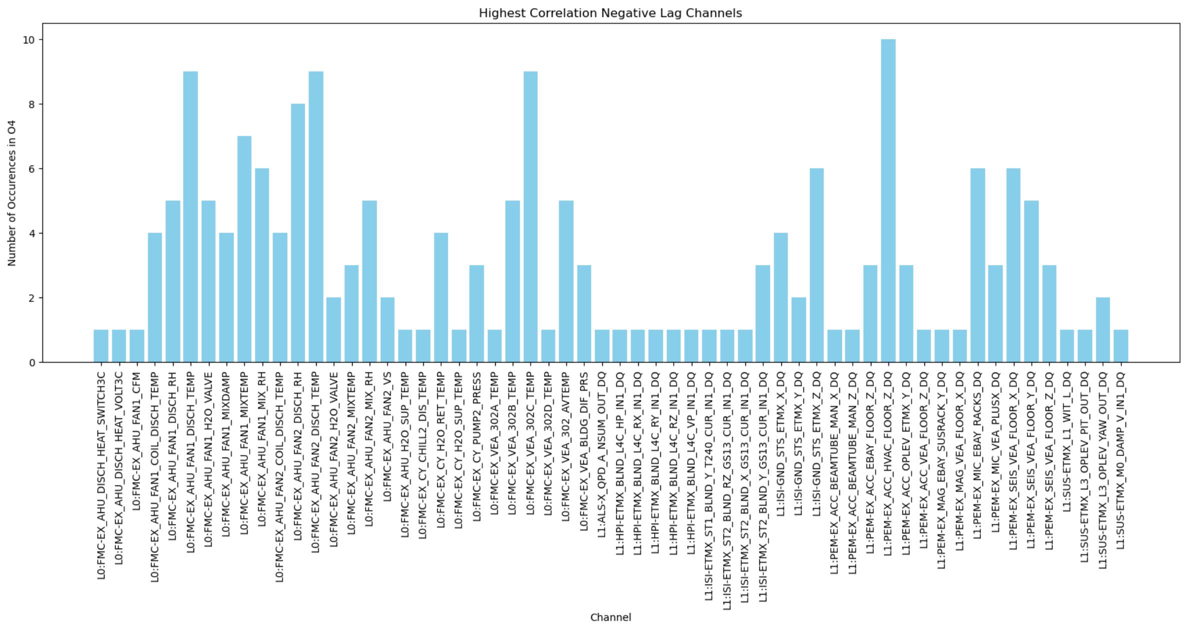



Figure 3: Bar graph that shows the number of times a channel has both a high correlation, negative lag, and consistently small (relative to the window duration) lag standard deviation.

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