LASER INTERFEROMETER GRAVITATIONAL WAVE OBSERVATORY
- LIGO -
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Tracking beam location on LIGO optics

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1 Introduction

The advanced LIGO (aLIGO) detectors succeeded in measuring gravitational waves on September 14, 2015, nearly one hundred years after Albert Einstein's initial prediction of the existence of oscillations in spacetime in 1916. The aLIGO detectors are a pair of simple (but very fancy) Michaelson interferometers that together detect these minute disturbances[5]. The differential arm length that is being measured is about 10^{-19} m when a gravitational wave passes by [4]. Because of the minuscule scale of the measurement, the detectors must be incredibly sensitive. This high sensitivity also means though, that the apparatus is susceptible to many other disturbances such as seismic vibrations, people living their lives nearby, and imperfections of the materials within the cavity–all of which contribute to noise in the measurement. Any disturbance in the data that looks like a signal, but is caused by something other than the quantity of interest, is noise.

One major source of noise in the experiment is angular motion of the optics [1]. Even very small rotation of optical elements significantly effects the differential arm length of the interferometer 1, such that the precision of the measurement is compromised[7]. If the beam is not perfectly centered on the mirror, the radiation pressure it exerts on the test mass can apply an additional torque on the optic, causing further angular rotation.

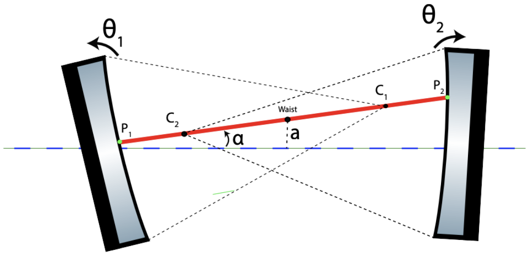

Figure 1: Fabry-Perot cavity with mirrors misaligned to show the change in beam travel due to angular motion of optics [7].

Currently there is no way to continuously monitor the position of the beam on all optics. In some places, Quadrant Photodiodes (QPD) can be placed behind mirrors, so the fraction of the beam that transmits through can be detected and tracked, but these can not be used anywhere where the beam needs to travel through the optic, like in the case of a beam splitter [3].

Ideally, the beam would be invisible on the surface of the test masses from any perspective other than the incident angle, because the mirrors would perfectly reflect all the 1064nm light. We live, however, in reality and not an ideal world, and some light does scatter off of the surface roughness and point defects that are present in the structure of the mirror coating, as can be seen in Figure 2 This is another source of noise in the experiment, as the scattered light can bounce around the cavity, recombining with the main beam and adding a random phase, but it can also be used as a tool, as it allows us to see where the beam is[3]!

Because the possibility of perfecting mirrors is far off in the distant future, this scattered light provides an opportunity to continuously track the location of the beam using a video

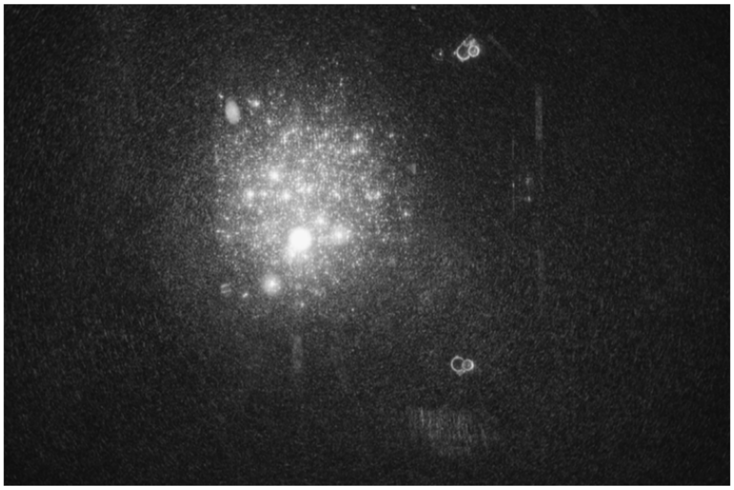

Figure 2: Image of aLIGO Test Mass (1.3 second exposure) [8]

imaging system, and then use that information about how the beam moves to calculate the angular noise and subtract it from the measurement.

2 Objectives

The goal of this project is to continue in previous efforts to track beam motion with sub pixel accuracy using the GigEcamera setup shown in Figure **??**.

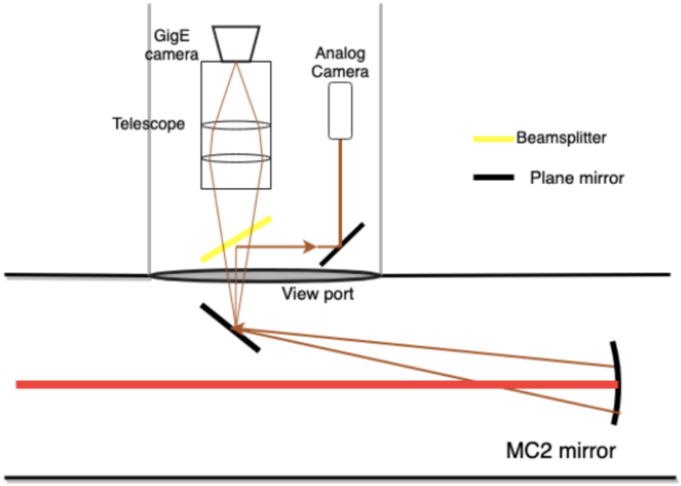

Figure 3: GigE camera at the MC2 optic of the Input Mode Cleaner cavity [2].

Past efforts included classical centroid detection, using contouring and center of mass calculations, but these methods failed to track a beam spot in real (noisy) data. The point scatters in the real images skew such calculations because as the beam moves, point defects don't, so as long as the beam is illuminating them, they are contributing disproportionately to the overall brightness of one area. The bottom of Figure **??** shows that when thresholding was used, these methods improved significantly, but not enough to serve as a robust solution to the beam tracking problem [2].

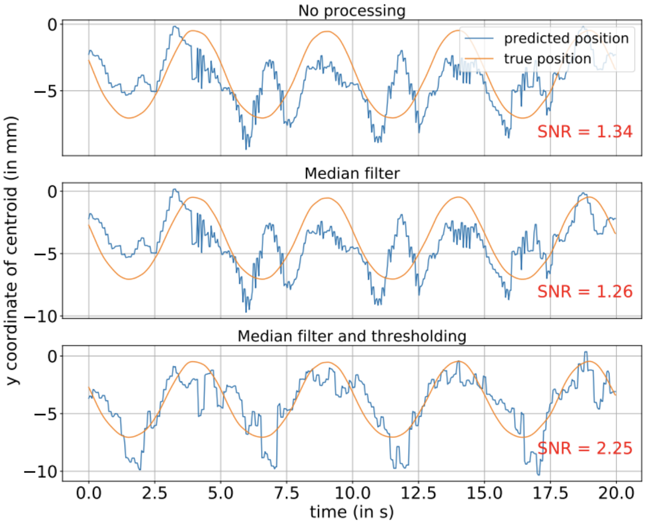

Figure 4: Center of mass tracking for GigE video from MC2 viewport [2].

When these approaches failed, the project turned to machine learning approaches, building Convolutional Neural Networks (CNN) trained on simulated beam spot motion that attempt to find a solution that would filter out the systematic error that results from the inhomogeneity in the data. There has been some success with this approach, but it has not yet been sufficiently carried out to be useful on real data. Past attempts succeeded in tracking the simulated beam spot motion of one millimeter, and we need to improve that by three orders of magnitude, with the real data [2].

Very basically, a CNN scans through an image and identifies elements of interest that might be present. Layers of the network manipulate the input information in various ways, one element at a time, and eventually, hopfully, convolve on an accurate result. Supervised neural networks are trained on a set of inputs labeled with their correct outputs, so that it learns weights that recognize the characteristics that are important. Then it can take a similar data set and (hopefully) label the inputs correctly.

3 Approach

Because real labeled data is limited, we will use a simulation of the beam spot to train the neural network. This simulation must be as close as possible to the actual imaging of the beam spot in order for the network to convolve with the real data. The simulation is currently of a uniform gaussian beam spot, moving in one dimension. We need to tune this to resemble the image that the camera will actually capture. The off axis camera will see a skewed gaussian beam of a more oblong shape, with point defects that glitter as the beam crosses over them. The intensity at the camera can be calculated by the Bidirectional Reflectance Distribution Function (BRDF).

$$BRDF = \frac{P_s/\Omega}{P_i \cos(\theta_s)} \tag{1}$$

where P_i is the incident intensity, P_s is the scattered power reaching the camera sensor, θ_s is the scattering angle and Ω is the solid angle subtended at the sensor. [**?**]

In order for the neural network to function, we have to train it on something whose expected output is known. The network will then learn from the simulated, labeled data set, training the weights within the layers of the network until it reliably succeeds in matching the input function of position in time[6]. The additional benefit to using a simulated data set to train the network is that the simulation can be layered and adjusted modularly. This will enable us to manipulate the simulation one component at a time and train the network in stages, turning switches on and off so that we can try to understand where and when the network fails, and hopefully figure out why fairly efficiently.

I am still curious about a classical approach that utilizes point defects–rather than being distorted by them–to track the motion of the beam. I am imagining an algorithm that uses point defects as anchors, to set some coordinates for the mirror, and then takes the difference between the intensities of point defects from one frame to the next to calculate the motion of the beam. I have been warned that everyone wants to try a classical approach and that they always fail... But I'm still tempted to make an attempt.

4 Project Schedule

Pre-arrival:Literature review. Continue to study the work that has been done previously, to deepen understanding of the details and the structures (networks and simulations) that have been created already.

Week 1-3: Modify beam simulation, accounting for off angle perspective and scattering from point defects.

Week 3-7: Study current neural network system, and train with simulation data.

Week 7-10: Test neural network on real data and troubleshoot.

References

[1] Peter R. Saulson, *Fundamentals of Interferometric Gravitational Wave Detectors Second Edition* World Scientific, Singapore (2017).

[2] Milind Kumar Vaddiraju, Mentors: Rana Adhikari, Gautam Venugopalan, Koji Arai, *Laser beam position tracking for LIGO interferometers.* LIGO-SURF Report (2019).

[3] Kruthi Krishna, Mentors: Gautam Venugopalan, Koji Arai, Rana Adhikari, *High Fidelity Probe of Optical Scatter from Point Defects.* LIGO-SURF Report (2019).

[4] `https://www.ligo.caltech.edu/page/vibration-isolation`

[5] `https://www.ligo.org/science/Publication-GW150914Detector/index.php#:~:text=The%20L%2Dshaped%20Advanced%20LIGO,miles%20(4%20kilometers)%20long.`

[6] `https://towardsdatascience.com/how-do-we-train-neural-networks-edd985562b73`

[7] Brian Seymour, Marie Kasprzack, Arnaud Pele, and Adam Mullavey, *Characterization of Nonlinear Angular Noise Coupling into Differential Arm Length of the LIGO Livingston Detector.* LIGO-DCC, Report (2017).

[8] L.Glover et al., *Optical scattering measurements and implications on thermal noise in Gravitational Wave detectors test-mass coatings* Physics Letters A. 382. (2018)