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Extending the Reach of Gravitational-wave Detectors with Machine Learning

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Abstract

This proposal presents the idea of using current machine learning techniques and algorithms to reduce the overall noise floor of the LIGO detectors. There will be a hard emphasis on techniques that analyze time series data, such as utilizing long short-term memory and non-linear regression algorithms. While other sources of noises in the detectors are outlined in the proposal, there will be a focus on using machine learning algorithms to hone in on noise sources coming from the physical attributes of the instrument itself. The goal is to increase the sensitivity of the detectors by subtracting linear and non-linear noise coupling mechanisms.

1 Introduction

In recent years LIGO has made strides in the discovery of gravitational waves from stellar mass black holes and neutron star mergers. However, there are still many more waves viable for detection below the current surface of noise. With the application of machine learning algorithms to the gravitational-wave detector data and auxiliary channels on-site, there is a possibility to reduce the noise in the time-series due to instrumental artifacts. By reducing the current noise floor there will be greater sensitivity in the instrument, leading to a greater rate of detection.

2 Machine Learning Techniques

There are two types of noise which contribute to the overall sensitivity of the detector. Non-removable noise sources, such as thermal noise, determine the underlying sensitivity of the detector. These noise sources can only be removed by improving the design of the detector itself. Other noise sources, known as removable noises, such as seismic noise, can be removed by monitoring the witness channels. Witness channels are the channels that monitor the physical environment around the detector. Machine learning algorithms coupled with data from the witness channels can be used on removable noise sources while keeping the signals we want to detect intact. By running the algorithms on past data, noise regression algorithms will be able to predict future noise sources and subtract them from the incoming data. It is also important to define neural networks as a set of algorithms that are designed to recognize patterns. These networks are made up of multiple layers that do different computations on the passing inputs, reducing the outputted data. These layers are identified as the input layer, the hidden layer where computations are preformed, and the output layer.

2.1 Time Series Forecast

Time series data is defined to be taken sequentially. Time series forecasting is the process of predicting future events based on previous data. The most important components of time series are the trend, cycle, seasonality and error. This type of forecasting will be used on the time series data outputted by the detector to analyze the witness channels and the environmental factors contributing to removable noise sources.

2.2 Long Short-Term Memory

Long Short-Term Memory networks are a type of recurrent neural network that process sequential inputs, taking into consideration past inputs to analyze the current input. This process is appealing because it can capture long-term dependencies in the data. Some of the removable noise sources, like seismic waves, will take several seconds to get to the witness channels, so having the ability to take in longer inputs is needed.

2.3 Nonlinear Regression

Nonlinear regression is used to find nonlinear relations between sets of data. It is ideal for the task at hand because it can estimate models with arbitrary relationships between independent and dependent variables.

3 Current Noise Sources

Glitches in the data can sometimes mimic astrophysical events, causing confusion in detecting gravitational waves. The causes of glitches can be identified through analyzing the witness channels during the time of the glitch and comparing multiple similar glitches within the same channel. Past glitches can be attributed to phone rings, airplanes, and trucks passing by. These glitches are examples of removable sources that machine learning techniques can be trained to learn and remove from the outputted data.[2] When picking which witness channels to subtraction from the data in order to get rid of certain glitches, they must be determined incapable of subtracting potential gravitational-wave signals. This can be tested by inserting simulated signals into a test data set and then processing them accordingly.

4 Physical Intuition

Rather than solely focusing on the environmental factors as causes for noise and glitches, looking into the instrument itself can lead to other sources for noise. The LIGO detector is very sensitive and must have passive vibration isolation, which is achieved through mechanisms such as a system of pendulums. It must also have active vibration isolation which is achieved through LIGO's active damping systems, consisting of various suspensions. By subtracting noise from the instrumental noise, LIGO detectors will have an increased sensitivity

4.1 Beam size and Angle

An instrumental cause of small fluctuations in the data is the jittering of the pre-stabilized laser. [**?**] The jittering was introduced when upgrades were added to the subsystem. A high powered oscillator was added to the system in an effort to increase laser power. However, the high powered oscillator required continuous heat dissipation via water cooling. Vibrations originated from the water flow, introducing jitter into the beam angle and size, resulting in noise. Other efforts, such as adding sensors that measured radial beam distortions and thermal compensation systems were used to mitigate the noise from the jittering. However, the jitter remained causing noise throughout the second LIGO observation.

5 Approach

I will first generate a test data set that I will train the neural network on. This consists of creating a mock data set and injecting noise sources as well as gravitational wave signals. While testing, I will check to make sure that when removing noise sources, it does not remove any potential gravitational wave sources. I will then create and test the neural network. This will take the most time due to all the testing that is required to get the desired technique and algorithms. Once the network works adequately with the mock data, I will test on real LIGO data. During the process of working with the real LIGO data, I plan on analyzing where the noise sources that are being subtracting are originating from. In doing so, we can get a better intuition of what physical properties of the instrument are causing noise.

References

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