Gravitational Waves Detection using Deep Learning

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***Abstract*—Key challenge of real-time detection and parameter estimation of gravitational waves from compact binary mergers is the computational cost of conventional matched-filtering and Bayesian inference approaches. Time-series data from three LIGO Observatories are collected and preprocessed by taking the time difference and alignment into consideration. These signals are then whitened by removing Gaussian and white noise from the signals by applying signal processing filters like Constant-Q transform, Wiener filter, and bandpass filtering. The SNR of these signals is increased. Fourier transform is applied to the time-series data to convert it into the Frequency domain to efficiently figure out the essential frequencies. The waves are then used as training data for Deep Learning models like 1-D CNN, and regression CNN for detection and parameter estimation of the gravitational waves signal in the data. These results emphasize the importance of using realistic gravitational-wave detector data in machine learning approaches and represent a step towards achieving real-time detection and inference of gravitational waves.**

I. INTRODUCTION

Gravitational waves are a concept predicted by Einstein in his General Theory of Relativity. According to this popular scientific theory the universe is said to consist of 4-dimensions (3 space co-ordinates and a time co-ordinate). It states that space and time are interlinked together to form a space-time continuum. Here the universe is said to be a space-time fabric and that mass bends space-time. If mass bends space-time, then mass under acceleration must create ripples, or waves, in space-time. A massive object moving through space-time will create waves that ripple out across the Universe. These are gravitational waves. Every object in the universe that has mass and accelerates in space-time produces gravitational waves. These waves from even massive black holes are almost undetectable with the current technology that exists because they exist at a vast distance. Over the past decade, physicists along with engineers have progressed forward to build kilometer-long interferometers: the Laser Interferometer Gravitational-Wave Observatory (LIGO), which constantly monitors astrophysical and cosmological sources for gravitational waves.

LIGO's main goal is to capture gravitational wave signals but the complexities associated with it are numerous. The amount of data scientists have to work with are numerous. The use of conventional algorithms that either require manual assistance or use brute-force approaches for detection doesn't seem feasible when considering the range of data is taken into consideration. Even putting that aside, the main problem that is to be dealt with is that the strength of the signals isn't strong enough and the equipment capturing the data isn't sensitive enough to make accurate predictions. And the lack of information about these waves and it overall being a complex concept to recognise makes it as much harder.

With incredible development in areas of ML/DL a suitable ML/DL should be capable of detecting these waves at a greater accuracy than conventional matched-filtering and Bayesian inference approaches at a lesser computational cost.

The following sections of this paper are organized as follows: Sec. II presents the background and the related works. Sec. III describes the Methods used and architecture for this project. Sec. V concludes the work.

II. BACKGROUND AND RELATED WORK

A. Background

This is a relatively new area of work as these waves' existence was confirmed only a couple of years ago in 2015. Conventional machine learning algorithms might not be all that accurate considering the inconsistencies associated with the data. Simple machine learning algorithms might not be complex enough to recognize all the features that are needed to classify the relevant data.

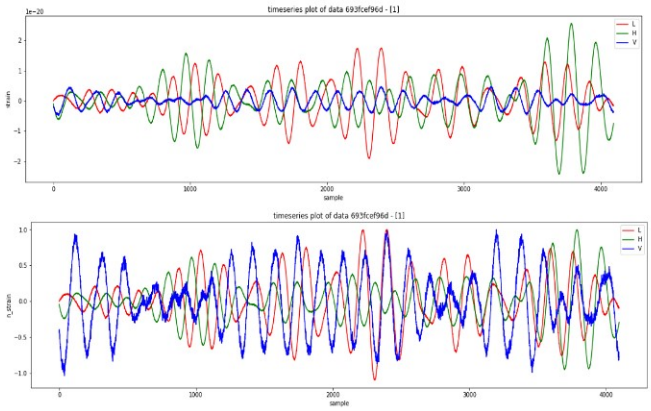

Fig. Unfiltered Signal Data from three LIGO observatories plotted parallelly for sample signal data.

Raw data from these observatories are often stationary and changes in signal data are very minute. The data being collected is prone to glitches caused by external sources. Since the data is very low in power slight vibrations from different sources (ground vibrations from nearby locomotives, etc.), EMR (Turning on switches, electronic noise, mobile radiation, etc.)) can cause it to be misrepresented. There is a need for this data to be preprocessed initially to filter out gaussian or white noise and increase the Signal to Noise Ratio (SNR). This preprocessed data is to be passed as input to the deep learning model that would, later on, classify the data.

B. Related Work

There has been use of different signal processing techniques and ML/DL algorithms for detecting these waves.

There has been implementation of signal processing techniques like wiener filter, bandpass filter, low pass filter, Deep Learning model to filter out noise from the data like deep filtering, etc.

ML algorithms like Decision Tree, SVM's, etc. were also used to classify the data. But these models aren't complex enough to accurately predict what is necessary. Variations in data is great enough to increase false positives and negatives.

Thus a combination of these noise filtering techniques are to be used to increase SNR and the data in frequency domain is passed as input to a suitable ML/DL model for prediction.

III. METHODS

For this project we've used the data set from Kaggle. The data set used has time-series data obtained from three LIGO (Laser Interferometer Gravitational-Wave Observatory) namely LIGO Hanford, LIGO Livingston, VIRGO. These three observatories are sampled at 4096Hz for 2s. These data are either a combination of detector noise or detector noise + GW signal.

The signal strength for most signals is very low for which we use multiple signal processing algorithms like whiten to remove gaussian noise, a low pass filter to filter out irrelevant higher frequencies. CQT filter is later applied on it and is passed as input to the 2-D CNN that we designed.

A. ArchitectureDiagram

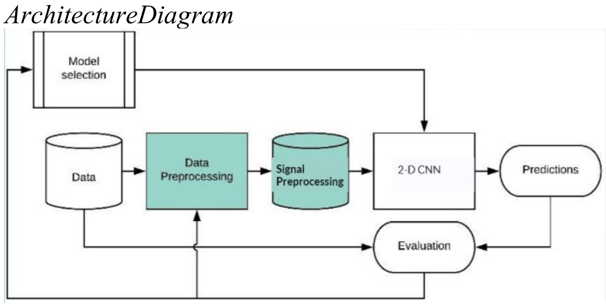

Fig. Architecture Diagram

a) Discrete Fast Fourier Transform (DFFT):

Discrete time-domain signals are transformed into discrete frequency domain signals using Discrete fast Fourier transform (DFFT)

b) Power Spectral Density (PSD):

A Power Spectral Density (PSD) is the measure of a signal's power level versus frequency(Hz). PSD's typically are used to characterize randomized broadband signals. The PSD's amplitude is normalized by the spectral resolution employed by digitize the signal.

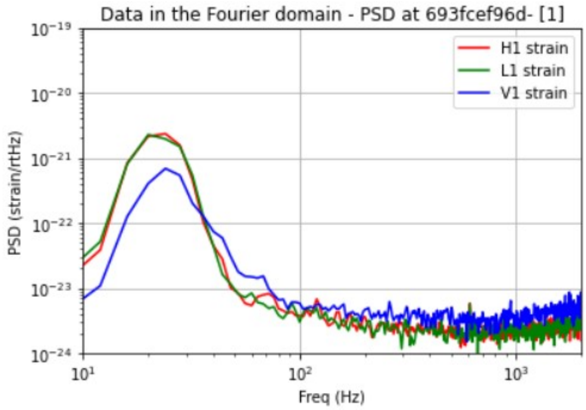

Fig. ASD for a sample signal

c) Amplitude Spectral Density (ASD):

The ASDs (Amplitude Spectral Density) are the square root of the PSD, which are averages of the square of the FFTs of the data. They are an estimate of the "strain-equivalent noise" of the detectors versus frequency, which limit the ability of the detectors to identify GW signals.

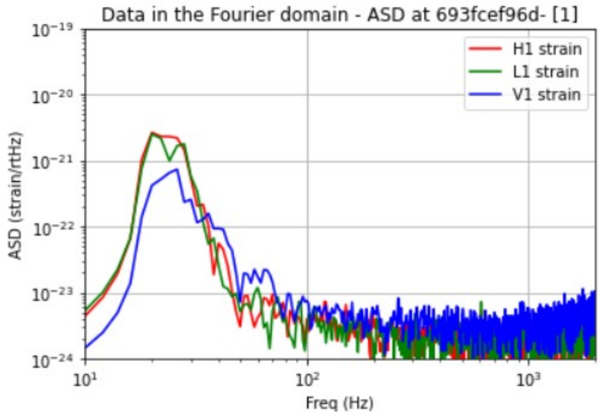

Fig. ASD for a sample signal

d) Low-Pass Filter:

It is a filter that passes signals with a frequency lower than a selected cutoff frequency and attenuates signals with frequencies higher than the cutoff frequency. The exact frequency response of the filter depends on the filter design.

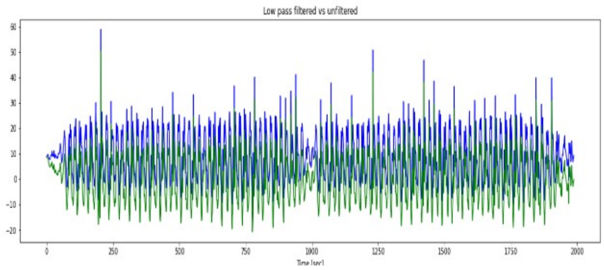

Fig. Low pass filtered vs unfiltered

e) Whitten:

A whitening transformation is a linear transformation that transforms a vector of random variables with a known covariance matrix into a set of new variables whose covariance is the identity matrix, meaning that they are uncorrelated and each has variance. This is used to remove gaussian or white noise form the detector signal data.

f) CQT Filter:

The constant-Q transform, simply known as CQT transforms a data series to the frequency domain.

The transform can be thought of as a series of filters f_k, logarithmically spaced in frequency, with the k-th filter having a spectral width δf_k equal to a multiple of the previous filter's width:

$$\delta f_k = 2^{1/n} \cdot \delta f_{k-1} = \left(2^{1/n}\right)^k$$

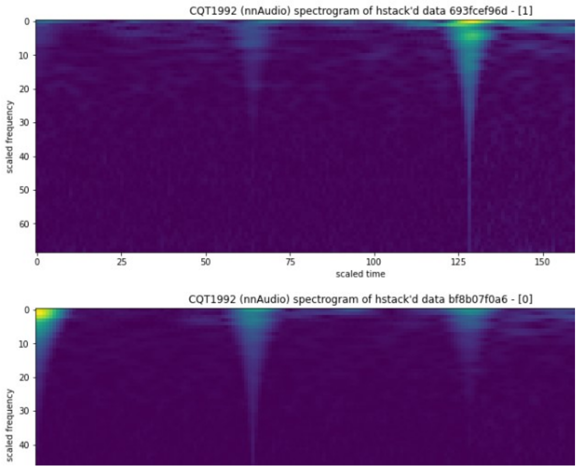

Fig.CQT Filtered Signal

B. DL Model

We’ve used a 2-D CNN for this. The 2-D CNN takes the preprocessed CQT passed LIGO data of shape (1,69,193,3). It outputs a regression value in the range [0,1].

The model has 3 Convolution layers of filter sizes (16,32,64). Max pooling is applied on every Conv layer to extract features from the data.

The outputs from Conv layers are flattened and passed as input to dense layers which reduce the output vector size. ReLu is used on the last but one dense layer. While Sigmoid activation is used to get a value in the range of [0,1].

To compare the performances of the model we have compared it against a 2-D CNN that also uses pre-trained weights from Efficient net. But this model outperformed it when it was compared for 1 epoch. This efficient net model had an accuracy of 52.85%.

It also was performing better when compared against 1-D CNN.

```
Model: "sequential"
_________________________________________________________
Layer (type)                 Output Shape
=========================================================
conv2d (Conv2D)              (None, 67, 191, 16)
_________________________________________________________
max_pooling2d (MaxPooling2D) (None, 33, 95, 16)
_________________________________________________________
conv2d_1 (Conv2D)            (None, 31, 93, 32)
_________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 15, 46, 32)
_________________________________________________________
conv2d_2 (Conv2D)            (None, 13, 44, 64)
_________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 6, 22, 64)
_________________________________________________________
flatten (Flatten)            (None, 8448)
_________________________________________________________
dense (Dense)                (None, 512)
_________________________________________________________
dense_1 (Dense)              (None, 128)
_________________________________________________________
dense_2 (Dense)              (None, 32)
_________________________________________________________
```

IV. Conclusion

The developed 2-D CNN model provides an alternative to conventional computationally expensive approaches. The model has a validation accuracy of 84.209% and an accuracy of 72.37% when tested for a data set consisted over 100000 files. Thus, we can conclude that DL approaches provide an efficient approach to detecting and recognizing gravitational wave parameters.

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