Distinguishing Between Cosmic Strings and Glitches in Gravitational-Wave Data Using a Neural Network

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January 22, 2025

Abstract

The detection of cosmic strings is important because reasons . The search for these comsic strings is being held back by detector glitches. These glithces can strongly resemble comsic strings. It is therefore very important to develop a method of distinguishing between a cosmic string signal and a glitch. In the work we focus on using a neural network for this task.

1 Introduction

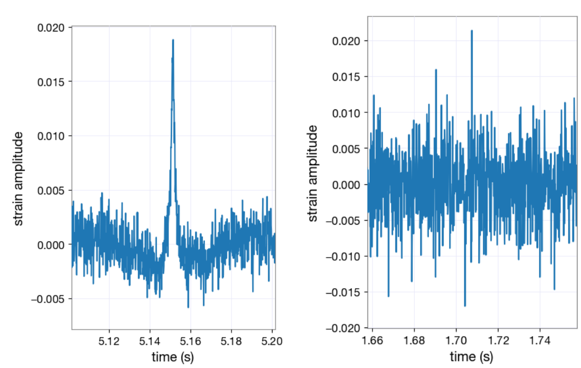
The first detected gravitational wave (GW) signal was GW150914[1] in 2015. These GW signals can originate from several sources, one of which is cosmic strings. Since the first observed GW many technological advancements have been made, yet one thing that still plagues detectors is the presence glitches. These are bursts of non-Gaussian noise that look like a signal . These glitches can be mistaken for a signal, so it is important to find a way to distinguish between a signal and a glitch. In this work we focus on the use of machine learning to distinguish between a glitch and a signal.

1.1 Cosmic strings

Cosmic strings are one-dimensional topological defects and originate form field theories [2]. These defects could have formed from spontanious symmetry breaking in the early universe [3]. These cosmic strings are of interest since they affect our understanding of physics, and can help confirm or rule out centrain physics models.

Cosmic strings appear at cosmological scales as thin strings with large densities, and their motion is well described by the Nambu-Goto action [4]. Cosmic stings can both be open strings or closed loops, and two cosmic strings are able to interact with eachother.

To detect cosmic strings we first need to understand what a GW signal with a cosmic string source looks like. Cosmic strings can produce GW signals in multiple ways. Examples include the formation of cusps and kinks [5]. Here we will focus on the cusps. A cusp is a singularity, where a point traveling along the curve would have to turn around. When this occurs, the physical string snaps into a cusp shape, and is instantaniously accelerated to the speed of light at that point. A burst GW is then emitted in the direction of acceleration [2]. Such a signal can be seen in the left plot in figure 1.



(a) The signal produced by the cusp of a cosmic string.

(b) Background noise with a peak.

Figure 1: Tha cosmic string signal and background noise.

With the knowledge of what the signal looks like, the next step is to search for a signal. The problem with the search for signals is that background noise can also form a peak, as can be seen in the right plot in figure 1. Since a GW signal from cosmic strings can be so similar to background noise, it is crucial to develop a method to distinguish between them.

1.2 Machine learning

2 Method

2.1 Data

The data used to train the neural network is computer generated data. There are two datasets; one with background noise and signals and one with just background noise.

2.2 Neural network structure

The proposed model used in this work is a convolutional neural network (CNN) designed for a bianry classification problem. The architecture, shown is Fig. X, extracts features from the input through seven convolution layers, followed by a fully conected layers that classify the input as either a signal peak or background noise. The network accepts three initial time series, coming from three diferent telescopes, which are transformed into a feature map by convolving them. This input data can be represented as a 3D tensor with shape (T, 1, 3) where T is the lenght of the time series, 1 is a single channel for each time step, and 3 denotes the number of imput features corresponding to the three telecopes.

After passing through a convolutional layer, the data is modified by the appliaction of a specfic chosen number N of kernels (also called filters). the kernels used have a shape of (k, input channels) with ks ranging from 3 to 7 (idk have to check.).

The kernels slide over the time axis of the input data, performing element-wise multiplications and then summing the elements. This produces a diferent feature map for each kernel which encodes specific patterns or correlations over the window defined by k.

The resulting ouput tensor has a shape (T', number of features map). T' is the length of the time axis after convolution, which depends on the kernel size, stride, and padding.

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3 Results

3.1 Accuracy

3.2 Efficiency

4 Discussion

5 Conclusion

References

[1] B.P. Abbott et al. (LIGO Scientific Collaboration and Virgo Collaboration). Observation of gravitational waves from a binary black hole merger. *Phys. Rev. Lett.*, 116:061102, Feb 2016.

[2] Quirijn Meijer, Melissa Lopez, Daichi Tsuna, and Sarah Caudill. Gravitational-wave searches for cosmic string cusps in einstein telescope data using deep learning. *Physical Review D*, 109(2), January 2024.

[3] Kai Schmitz and Tobias Schröder. Gravitational waves from cosmic strings for pedestrians, 2024.

[4] Mairi Sakellariadou. Cosmic strings and cosmic superstrings. *Nuclear Physics B - Proceedings Supplements*, Volumes 192–193, 2009.

[5] R. et al Abbott. Constraints on cosmic strings using data from the third advanced ligo–virgo observing run. *Phys. Rev. Lett.*, 126:241102, Jun 2021.