

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

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Abstract

The detection of cosmic strings is important because reasons . The search for these cosmic strings is being held back by detector glitches. These glitches can strongly resemble cosmic 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 of 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.

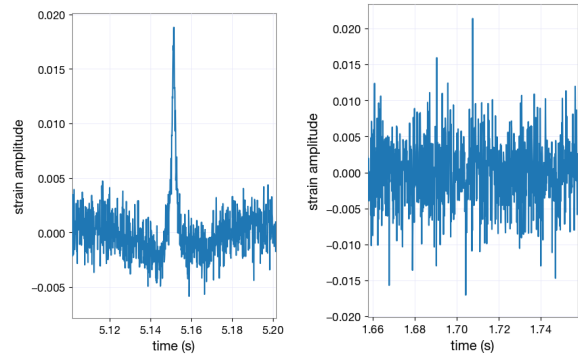
1.1 Cosmic strings and glitches

Cosmic strings are one-dimensional topological defects and originate from field theories [2]. These defects could have formed from spontaneous 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 certain 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 strings can both be open strings or closed loops, and two cosmic strings are able to interact with each other.

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 instantaneously 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: The signal and glitch plots side by side.

With the knowledge of what the signal looks like, the next step is to search for a signal. The problem with this is that the form of the signal is very similar to that of certain glitches, like the blip glitch. Blip glitches are short noise transients

with a large frequency bandwidth [6]. The form of this glitch can be seen in the right plot in figure 1

Since a GW signal from cosmic strings can be so similar to glitches, it is crucial to develop a method to distinguish between them.

1.2 Machine learning

2 Method

2.1 Data

2.2 Neural network structure

The proposed model used in this work is a convolutional neural network (CNN) designed for a binary classification problem. The architecture, shown in Fig. X, extracts features from the input through seven convolution layers, followed by a fully connected layers that classify the input as either a signal peak or background noise. The network accepts three initial time series, coming from three different 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 length of the time series, 1 is a single channel for each time step, and 3 denotes the number of input features corresponding to the three telescopes.

After passing through a convolutional layer, the data is modified by the application of a specific chosen number N of kernels (also called filters). the kernels used have a shape of $(k, \text{input channels})$ with k s 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 different feature map for each kernel which encodes specific patterns or correlations over the window defined by k .

The resulting output tensor has a shape $(T', \text{number of features map})$. T' is the length of the

time axis after convolution, which depends on the kernel size, stride, and padding.

3 Results

3.1 Accuracy

3.2 Efficiency

4 Discussion

5 Conclusion

References

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