Postprint: Architectural Complexity of Deep Learning Networks for Gravitational Wave Detection

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Abstract

The application of deep learning to gravitational wave detection has been a research hotspot in recent years. Matched filtering can be viewed as a single-convolution-layer neural network where templates are stored in convolution kernel parameters, and by deepening the model, similar detection performance can be achieved while significantly reducing the number of parameters. This work discusses deep learning gravitational wave detection models with different convolution kernel sizes, numbers of convolution kernels (model width), and numbers of convolution layers (model depth). Additionally, the detection performance of models employing batch normalization (BN) before the fully connected layer is investigated, revealing that the detection accuracy of single-convolution-layer models improves from approximately 50% to over 90% after adding BN. The research results provide a potential new method for compressing the number of matched filtering templates, suggesting that using BN layers and fully connected layers after matched filtering may significantly reduce the number of matching templates.

Full Text

Research on the Influence of Network Structure Complexity on Deep Learning for Gravitational Wave Detection

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Abstract

Deep learning for gravitational wave detection has emerged as a prominent research area in recent years. The matched filtering method can be viewed as a neural network with a single convolutional layer where templates are stored as convolution kernel parameters. By increasing model depth, similar detection performance can be achieved while substantially reducing the number of parameters. This paper investigates deep learning gravitational wave detection models with varying convolution kernel sizes, numbers of convolution kernels (model width), and numbers of convolutional layers (model depth). Additionally, we examine the detection performance of models employing batch normalization (BN) before the fully connected layer, finding that the detection accuracy of single-convolutional-layer models improves from approximately 50% to over 90% after incorporating BN. These results provide a potential novel approach for compressing the number of matched filtering templates, suggesting that adding BN and fully connected layers after matched filtering may significantly reduce template requirements. The generalization capability of optimized CNN models on different background noise is also investigated. We find that models trained on data with H1 background noise can be applied to detect data with L1 background noise, though the accuracy decreases slightly.

Keywords: binary black hole merger; gravitational wave detection; deep learning

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1. Introduction

On September 14, 2015, the Laser Interferometer Gravitational-wave Observatory (LIGO) achieved the first direct detection of gravitational waves in human history, designated GW150914. This event originated from the merger of two black holes located 1.3 billion light-years away. The successful detection of gravitational waves directly validated Einstein's general relativity predictions and opened a revolutionary observational window into the universe—gravitational wave astronomy [1]. On August 17, 2017, humanity observed gravitational wave signals from a binary neutron star merger, GW170817, for the first time [2]. Approximately 1.7 seconds after the merger signal detection, the Fermi Gamma-ray Burst Monitor detected a gamma-ray burst [3–5], and numerous observatories worldwide subsequently detected electromagnetic signals across multiple bands [6]. This marked the first unambiguous joint observation of gravitational and electromagnetic radiation from a single astrophysical source, heralding the era of multi-messenger astronomy.

Ground-based laser interferometer detectors operate in the sensitive frequency band of 10–10^3 Hz, primarily detecting gravitational wave signals from binary neutron star and stellar-mass black hole mergers. Space-based gravitational wave detectors are also under development, with detection frequencies ranging from 10^{-4} to 1 Hz, focusing on numerous double white dwarf systems in the

Milky Way and extreme/intermediate mass-ratio binary systems. The Laser Interferometer Space Antenna (LISA) has been selected as the European Space Agency's L3 mission [7], while China's TianQin [8] and TaiJi [9] projects are also in planning. On August 31, 2019, the microgravity technology experimental satellite "TaiJi-1" was successfully launched from Jiuquan Satellite Launch Center, with all tests proceeding normally. On December 20, 2019, the first technical experimental satellite of the TianQin project, "TianQin-1," was successfully launched from Taiyuan Satellite Launch Center. Currently, the LISA Pathfinder, TaiJi-1, and TianQin-1 experimental satellites have all operated successfully, and space-based gravitational wave detectors are expected to be operational in the 2030s, ushering in the era of multi-band gravitational wave detection.

Gravitational wave detection requires collaborative efforts across mathematics, physics, computer science, and other disciplines [10]. LIGO's sensitivity reaches the 10^{-22} level, with background noise typically exceeding gravitational wave signals. Transient gravitational wave patterns must be identified through data analysis pipelines, including PyCBC [11], GstLAL [12], and SPIIR [13], which run on approximately 70,000 CPU cores and thousands of high-performance GPUs across institutions such as Caltech, MIT, and the Hanford and Livingston observatories.

The matched filtering algorithm SPIIR, developed collaboratively by researchers from China, Australia, and the United States [13], constructs matched filters from parallel time-shifted first-order IIR filters, mapping template library templates to numerous time-shifted IIR filter parameters for easier parallelization and scalability. Gravitational wave data analysis pipelines operate in both offline and online modes, with the latter achieving data processing latencies on the order of minutes. Multi-messenger astronomy requires even lower computational latency, as real-time sky localization can be shared with electromagnetic telescopes for rapid follow-up observations. Machine learning methods have already been integrated into LIGO's data processing pipeline. LIGO analyzes approximately 5,000 fast and 200,000 slow data channels to assess signal quality, and transient noise from nonlinear coupling of 60 Hz AC power has been successfully removed using machine learning [14]. We believe machine learning will inevitably be applied to gravitational wave detection, localization, and source parameter inversion. Deep learning is expected to be integrated into gravitational wave data analysis pipelines, replacing low-latency matched filtering analysis and facilitating real-time gravitational wave detection.

Deep learning has achieved remarkable success in computer vision, audio signal processing, and medical diagnosis, while its application to gravitational wave data processing remains exploratory. In 2018, Gabbard et al. [15] and George and Huerta [16] independently discovered that deep learning could achieve matched filtering accuracy in gravitational wave detection, with substantially improved computational efficiency, promising real-time transient gravitational wave pattern detection. Subsequently, George and Huerta [17] applied deep learning models to real LIGO noise signals, finding consistent performance with simulated noise. Recent research on deep learning for gravitational wave detection can be categorized into model optimization, application expansion, application refinement, and mechanism studies.

In 2019, Gebhard et al. [18] employed dilated convolutional neural networks for gravitational wave detection, demonstrating effective detection of compact binary coalescence signals. In 2020, Wang et al. [19] introduced a matching-aware layer to convolutional neural networks, creating a novel architecture whose perception layer simulates matched filtering using dozens of waveform templates. Li et al. [20] optimized Gabbard's model by preprocessing signals through wavelet decomposition and parameter adjustment. Luo et al. [21] found that modifying dropout layers could improve detection accuracy. Deighan et al. [22] used genetic algorithms to optimize George and Huerta's model, achieving 11% higher accuracy with only 78% of the original parameters. In 2021, Xia et al. [23] investigated the generalization capability of CNN architectures for gravitational wave detection, optimizing George and Huerta's model through dropout and BN, and demonstrating that models exhibit different output statistical characteristics for different input parameter spaces. Huerta's team integrated two CNNs to create a new model capable of concurrent analysis of gravitational wave detector network data [24].

Beyond compact binary gravitational wave signal detection, researchers have applied deep learning to source parameter prediction and localization [25–28], gravitational wave denoising [29,30], continuous gravitational wave detection [31], and stellar collapse gravitational wave detection [32,33]. In 2019, Huerta's team constructed deep models to predict binary system masses and spins, achieving results consistent with Bayesian analysis but with significantly reduced analysis time—model prediction time was only 2 ms on a single Tesla V100 GPU [25]. In 2020, they extended WaveNet, originally applied to speech signal processing, to gravitational wave denoising [30]. Fan et al. [26] innovatively integrated gravitational wave detection and source parameter estimation into a single model, investigating how detection accuracy varies with the number of observatories. In 2021, Chongqing University's Li Jin team employed machine learning to analyze pulsar timing array signals, studying nanohertz-band gravitational wave detection [34].

This paper investigates the impact of different network structure complexities on deep models for gravitational wave detection, using real LIGO O1 noise data as a foundation. Section 2 reviews the mathematical formulations of matched filtering and convolutional neural networks, revealing their consistency. Sections 3 and 4 describe the datasets and model architectures used for training and testing. Section 5 presents and analyzes experimental results.

2.1 Matched Filtering Method

Under the assumption of stationary Gaussian additive background noise, matched filtering yields the optimal linear gravitational wave detection method. Let s(t) be the strain signal acquired by LIGO and hi(t)   T be the matching template, where T represents the template library. The matched filter output corresponding to template hi(t) is:

$$z_i(t) = \int \frac{\tilde{s}(f)\tilde{h}_i^*(f)}{S_{dn}(f)} e^{j2\pi ft} df$$

where $\tilde{s}(f)$ and $\tilde{h}_i^*(f)$ are the Fourier transforms of s(t) and hi(t), respectively. $S_{dn}(f)$ is the two-sided power spectral density of the signal, related to the one-sided power spectrum $S_n(f)$ by:

$$S_n(f) = \begin{cases} 2S_{dn}(f), & f > 0 \\ 0, & f < 0 \end{cases}$$

Define:

$$x(t) = \int \frac{\tilde{s}(f)}{S_n(f)} e^{j2\pi ft} df$$

Then the matched filter output for template hi(t) becomes:

$$z_i(t) = \int x(\tau) h_i(t-\tau) d\tau$$

LIGO acquires discrete-time strain data s[n] = s(nT), where T is the sampling period. Discretizing the above equation yields:

$$z_i[n] = T \sum_m x[m] h_i[m-n]$$

where $h_i[n] = h_i(nT)$. The matched filter output is:

$$z[n] = \max_i (z_i[n])$$

2.2 Convolutional Layers in Convolutional Neural Networks

Convolutional neural networks consist of input, output, and multiple hidden layers. Hidden layers can be stacked through convolution, pooling, fully connected layers, etc., with each layer functioning as a system with inputs and outputs. A convolutional layer is defined by its kernel size and number. Assuming the convolutional layer input is x[n] and the ith convolution kernel is wi[n], its output [35] is:

$$y_i[n] = \sum_m x[m]w_i[n-m]$$

Let $r_i(t) = h_i(-t)T$. Equation (5) becomes:

$$z_i[n] = \sum_m x[m]r_i[n-m]$$

Comparing equations (7) and (8), we conclude that matched filtering can be viewed as a convolutional neural network model with a single convolutional layer (where convolution kernel parameters constitute the matching template library).

2.3 Necessity of Studying Model Width and Depth

We define the number of convolution kernels per layer as the model's width and the number of convolutional layers as the model's depth. Matched filtering represents a convolutional neural network that is very wide but has only one layer. Direct signal-template matching in matched filtering suffers from low computational efficiency. Existing deep learning gravitational wave detection models improve efficiency by increasing model depth to reduce parameter count. According to current LIGO design sensitivity, gravitational wave detection models must maintain extremely low false alarm probabilities, as low as one in ten thousand, to be applicable. Before deployment in online real-time detection, comprehensive optimization studies of deep learning gravitational wave detection methods are essential. Whether convolutional neural networks can balance efficiency and reliability through width-depth trade-offs remains an open question. This paper investigates the performance of deep models with varying width and depth for gravitational wave detection.

3. Dataset

The dataset in this study was generated using the open-source program ggwd [18]. It comprises two classes: one containing only real LIGO noise and another containing noise plus gravitational wave signals. Noise was randomly extracted from H1 data (excluding detection events), while gravitational wave signals were generated using the SEOBNRv4 waveform approximation method. Each training sample has a duration of 1 s and a sampling frequency of 4096 Hz. The ranges of source parameters and signal-to-noise ratios in the dataset are shown in Table 1 . Figure 1 [Figure 1: see original paper] displays examples of both data classes: Class 0 contains detector noise only, while Class 1 shows detector noise injected with gravitational wave signals. When simulating binary black hole merger waveforms using the SEOBNRv4 model, we fixed the source distance at 100 Mpc. However, this distance becomes irrelevant in the final composite signal because the binary black hole merger signal is scaled according to a predefined signal-to-noise ratio before injection into the background noise.

4. Deep Learning Gravitational Wave Detection Model

The deep learning gravitational wave detection model used in this paper comprises input, hidden, and output modules. The input module receives whitened strain data, while the output obtains binary classification values through a fully connected layer and Softmax activation. The hidden module is constructed by stacking basic units built from convolution, ReLU activation, and max pooling, as illustrated in Figure 2 [Figure 2: see original paper]. The network complexity of the models discussed in this paper is determined by three parameters: convolution kernel size, number of convolution kernels, and number of basic units in the model. The number of basic units in the hidden layer determines the model depth, while the number of convolution kernels in each basic unit determines the model width. Additionally, we investigate models where the final basic unit is optimized with batch normalization (BN).

Figure 3 [Figure 3: see original paper] shows the system block diagram of a gravitational wave detection model composed of three basic units. Table 2 lists the parameter values studied in this paper.

5. Experimental Results

The performance of deep learning gravitational wave detection models depends on both architecture and training set size. All experiments in this paper were conducted using four training set sizes: 4,800, 20,000, 35,000, and 50,000 samples. The variation of optimal model depth with training set size is shown in Tables 3 and 4 . For both kernel sizes of 8 and 16, the optimal training set size is 50,000. Therefore, subsequent analyses in this paper focus on models trained with 50,000 samples.

5.1 Impact of Model Depth and Width on Gravitational Wave Detection By adjusting convolution kernel size, model width, and model depth, we constructed various deep network models for training and testing. The results are listed in Tables 5 and 6 . The experiments demonstrate that models with more convolution kernels per layer (greater width) require smaller optimal depth. For example, with a kernel size of 8, the optimal depth is 6 for width 8 but only 3 for width 32. This indicates that detection performance can be optimized through comprehensive adjustment of both model depth and width.

5.2 Impact of BN Optimization on Gravitational Wave Detection We also investigated the effect of adding batch normalization (BN) after the final basic unit. After incorporating the BN layer, we examined the gravitational wave detection capability of models with different depths. Figure 4 [Figure 4: see original paper] shows the variation in detection accuracy with model depth before and after adding BN. We found that adding a BN layer significantly improves the detection accuracy of shallow gravitational wave detection models with depths of 1 and 2. For instance, at depth 1, detection accuracy increases from 51% to 94%. As analyzed in Section 2, a depth-1 CNN can be viewed as matched filtering followed by a fully connected layer. This experimental result provides a new approach for optimizing matched filtering, potentially enabling substantial template count reduction while maintaining detection performance, thereby achieving real-time detection. Figure 5 [Figure 5: see original paper] shows ROC curves for models of different depths before and after BN addition. Comprehensive analysis of Figures 4 and 5 reveals that BN is less effective for deep feature optimization and may even degrade network detection performance.

To explore whether the impact of BN layers on different-depth models depends on detector operating conditions, we repeated the training and testing using L1 detector noise data with identical methodology. The experiments yielded similar results to those obtained with H1 data. Figure 6 [Figure 6: see original paper] shows the variation in gravitational wave detection accuracy with model depth before and after BN addition for L1 background noise, demonstrating that single-layer CNN detection accuracy improves from 50% to 91% after BN incorporation.

5.3 Generalization Study of Models with BN Layers Furthermore, to verify the generalization capability of models with BN layers, we tested models trained on H1 background noise data on L1 background noise data. The results are shown in Figure 7 [Figure 7: see original paper]. We found that models trained on H1 data can be applied to L1 data detection, but with reduced generalization capability. For example, a single-layer neural network achieves 94% detection accuracy on H1 data, which decreases to 89% on L1 data.

6. Conclusion

Gravitational wave detection is crucial for studying the origin and evolution of black holes. This paper investigates the application of convolutional neural networks with varying depth and width hyperparameter spaces to gravitational wave detection. To exclude training set size effects, we employed four training set scales: 4,800, 20,000, 35,000, and 50,000 samples. Our experiments reveal that models with more convolution kernels per layer (greater width) require smaller optimal depth. Model performance can be optimized through comprehensive adjustment of depth and width. Shallow single-layer and double-layer models without BN optimization exhibit poor gravitational wave detection performance, but incorporating BN significantly improves their accuracy from approximately 50% to over 90%. These results provide a potential new method for compressing matched filtering template counts, suggesting that adding BN and fully connected layers after matched filtering may substantially reduce template requirements. However, since adding BN before the fully connected layer in multi-layer CNN models may reduce detection accuracy, the depth at which BN is placed can affect detection performance.

Note: Figure translations are in progress. See original paper for figures.