Denoising Gravitational Waves with Enhanced Deep Recurrent Denoising Auto-Encoders

Hongyu Shen, Daniel George, Eliu. A. Huerta, Zhizhen Zhao

Department of Electrical and Computer Engineering, National Center for Supercomputing Applications, University of Illinois at Urbana-Champaign

INTRODUCTION

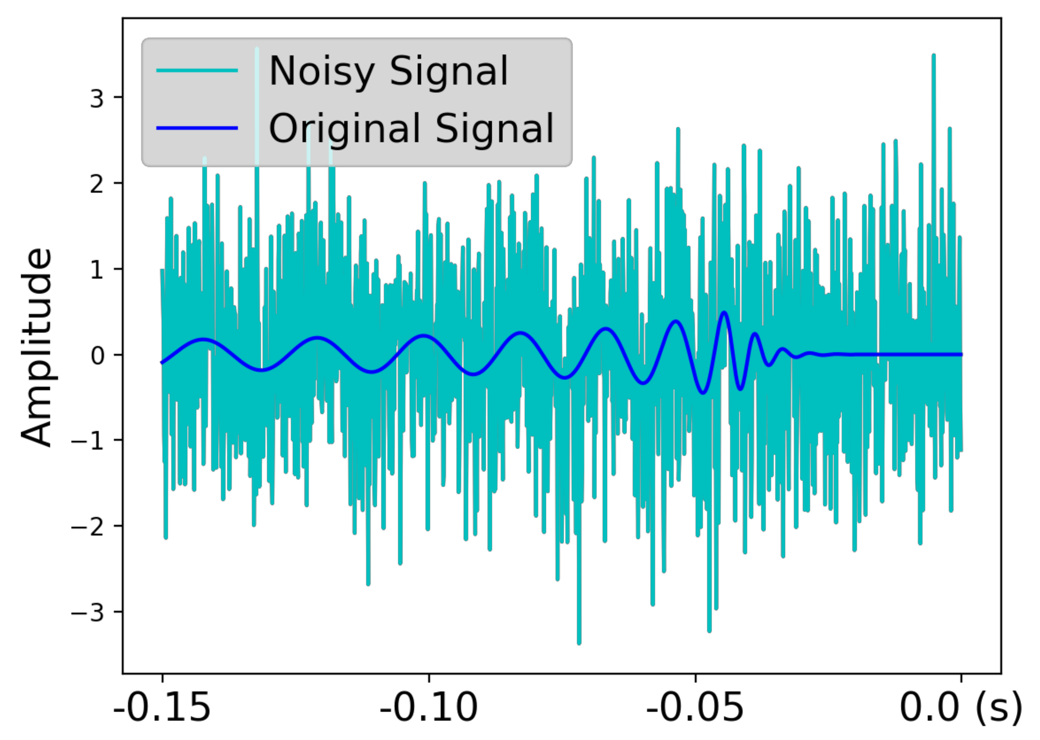
Denoising of time domain data is a crucial task for many applications such as communication, translation, virtual assistants etc. For this task, a combination of a recurrent neural net (RNNs) with a Denoising Auto-Encoder (DAEs) has shown promising results. However, this combined model is challenged when operating with low signal-to-noise ratio (SNR) data embedded in non-Gaussian and non-stationary noise. To address this issue, we design a novel model, referred to as **Enhanced Deep Recurrent Denoising Auto-Encoder** (EDRDAE), that incorporates a signal amplifier layer, and applies curriculum learning by first denoising high SNR signals, before gradually decreasing the SNR until the signals become noise dominated. We showcase the performance of EDRDAE using time-series data that describes gravitational waves embedded in very noisy backgrounds. In addition, we show that EDRDAE can accurately denoise signals whose topology is significantly more complex than those used for training, demonstrating that our model generalizes to new classes of gravitational waves that are beyond the scope of established denoising algorithms.

Notice: Here we use a different SNR, peak SNR, which is defined as:

$$\mathrm{SNR}_{\mathrm{peak}} = \frac{\text{Maximum value of a given signal}}{\text{Standard deviation of noise}}$$

AIM

Gravitational waves received by LIGO detectors are inevitably contaminated by non-Gaussian and non-stationary noise. The scale of the noise is usually far greater than one for the gravitational waves, as shown in the figure below. Conventional denoising algorithms fail to handle this extremely noisy case. As a result, we want to take advantage of deep learning technology, designing a good model to remove noise and return clean waveforms with high quality. Meanwhile, we also want to make sure when there is no signal in the input, the model is able to prevent false positive.



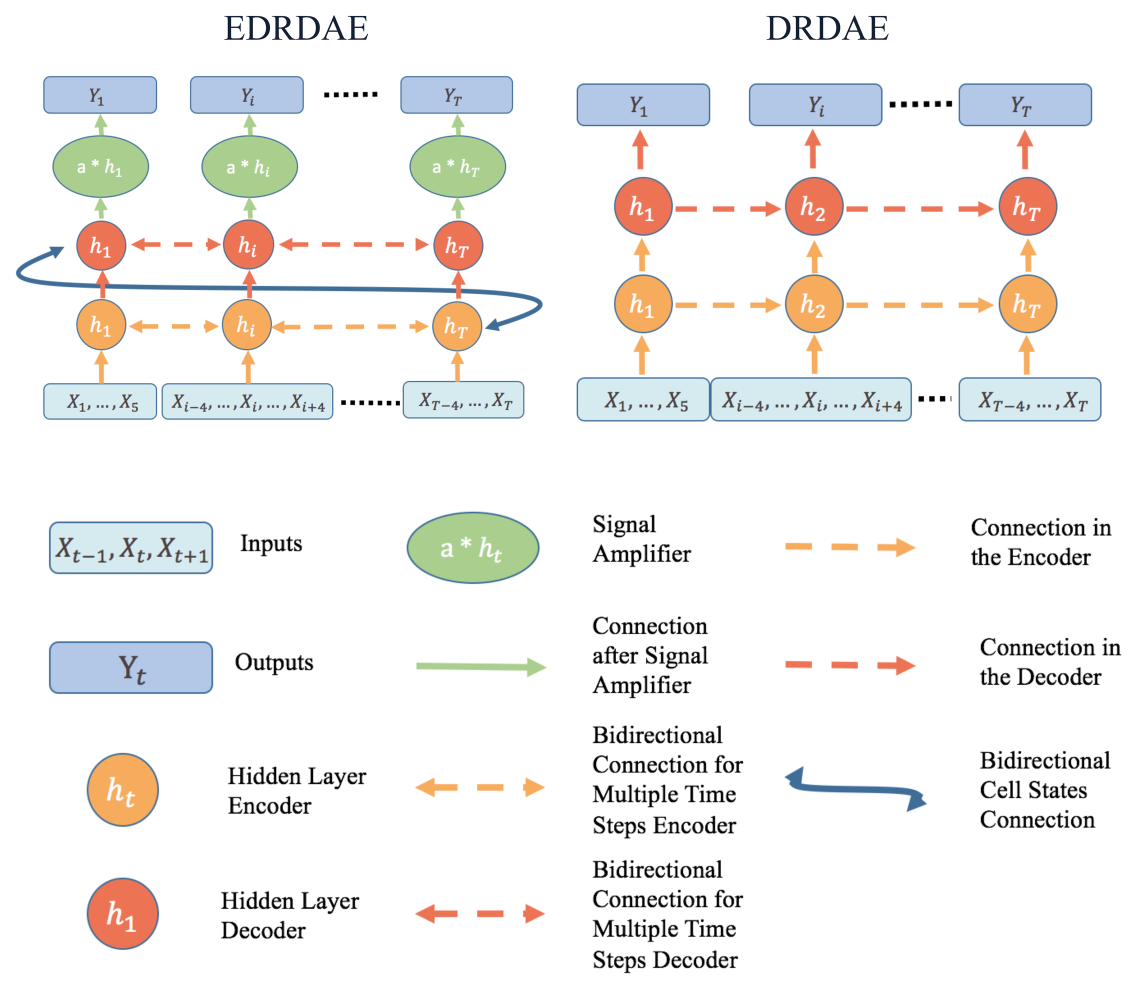
METHOD

The architecture of EDRDAE empowers this new deep neural net to better denoise time series embedded in non-Gaussian and non-stationary noise datasets. There are three major structural highlights compared to DRDAE:

(1). We apply bidirectional LSTMs rather than conventional one-way LSTMs, since the bidirectional structure will pass the information of the input data through time in two directions, forward and backward. Especially for multiple time step inputs, where we use several neighboring time points to predict the central time step, we found bidirectional layers to help pass information from neighboring time steps (before and after the central time step) to adjacent layers. Intuitively, this boosts denoising performance significantly.

(2). The introduction of the Signal Amplifier (SA). It is beneficial in denoising signals when the amplitude of the signal is lower than that of the background noise. This new structure is inspired by speech data, which is nearly symmetric concerning the mean-value axis (a horizontal line). SA right before the output layer assists the network in learning more evident patterns and magnifying the reconstructed values to reach the true values of the clean references.

(3). We apply a cross-layer connection, which is in spirit similar to the connection in It passes through both forward and backward cells in bidirectional layers. The cell states from the output time step of the encoder are passed to the cell states of the first time step of the decoder layer, using blue arrows. Empirically, we observe this structure helps reconstruction in noisy environments and achieves higher accuracy compared to models that have different cell states for different layers.



EXPERIMENT

Dataset Preparation

We designed experiments to illustrate the performance of DRDAE (an old comparing model) and EDRDAE on GW datasets. We use simulated GWs describe binary black hole (BBH) mergers, generated with the waveform model available in LIGO's Algorithm Library. We consider BBH systems with mass-ratios q 10, and with total mass between 5 and 75 in the unit of solar mass. The waveforms are generated with a sampling rate of 8192 Hz. We consider the late inspiral, merger and ring-down evolution of BBHs, since it is representative of the BBH GW signals reported by ground-based GW.

The SNR of astrophysical GW sources in the LIGO detectors cannot be known prior to detection. Therefore, we normalize our data to have variance 1.0. In addition, we also add random shifts to the training data, to make the model more resilient to variations in the location of the signal. For every input signal, we randomly generate an integer between 0 and 200 as shift length for left and right shifts. The length is 0% to 15% proportional to the total signal length. Zero padding is performed when necessary.

Decreasing SNR (Curriculum Learning)

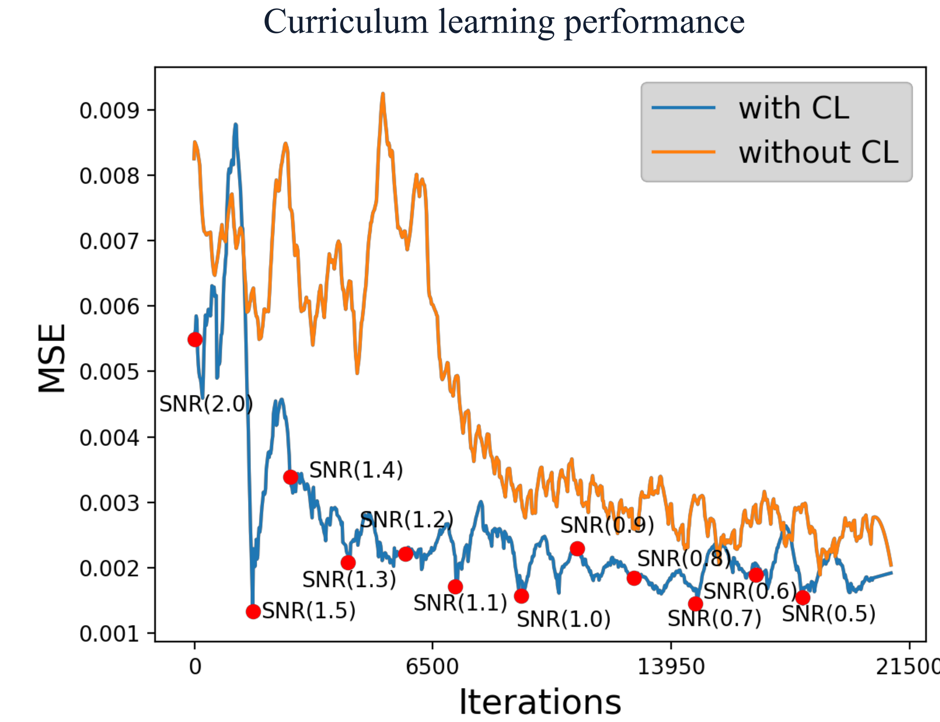
Different from the conventional image and audio denoising setups for which the noise level is typically too low to obscure image background or audio utterances, the data we focus on, however, are always embedded within extreme noise. For example, raw gravitational waves. As a result, it is difficult to learn the original signal structure and remove the noise from raw data when training directly starts with very low SNRs. We found that gradually reducing SNRs during training, an idea taken from curriculum learning literature, provides regularization, which allows the network to distill more accurate information of the underlying signals with larger SNRs to signals with lower SNRs.

The following table and the plot shows how we perform the curriculum learning during the training, and the reconstruction loss comparison for models with and without this learning strategy.

Curriculum learning configurations

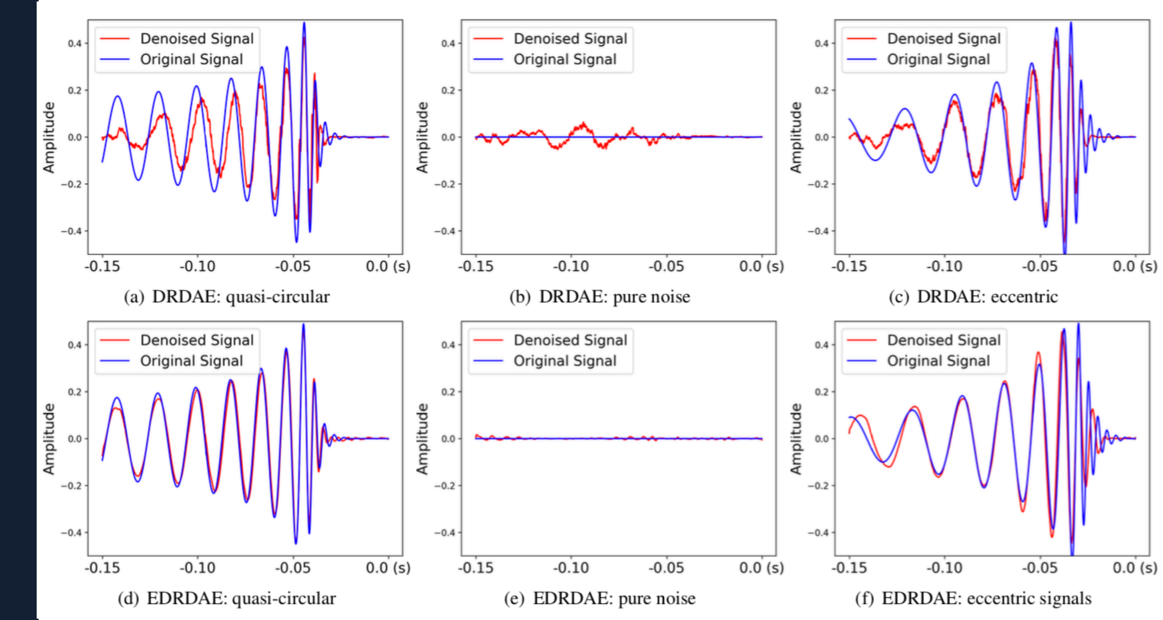
ITER. (K)	2	3	4.5	6	7.5	9	10.5	13	14.5	16	17.5
$\mathrm{SNR}_{\mathrm{peak}}$	1.5	1.4	1.3	1.2	1.1	1.0	0.9	0.8	0.7	0.6	0.5

Curriculum learning performance



MODEL PERFORMANCE

DRDAE v.s. EDRDAE



Compare to other popular approaches

Comparisons of MSE and overlap across different approaches. •/• refers to "metric for quasi-circular" / "metric for eccentric". Here "DL" refers to dictionary learning. "WT" refers to wavelet thresholding.

MODEL	PCA	DL	WT	DRDAE	EDRDAE
MSE	.033/.034	.108/.107	.017/.018	.008/.004	.001/.005
OVERLAP	.644/.639	.466/.476	.684/.671	.906/.955	.994/.985

CONCLUSIONS

In this paper, we proposed a new deep recurrent denoising auto-encoder to denoise gravitational wave signals contaminated by an extremely high level of noise often encountered in realistic detection scenarios. By introducing additional structures to the model (cross-layer connection, signal amplifier), and by adopting a training approach that gradually reduces the SNRs of the training samples, we show that our model outperforms DRDAE and other tested popular denoising algorithms (PCA, dictionary learning and wavelet thresholding) for GW denoising. It is also noteworthy that although our denoising auto-encoder was only trained with quasi-circular GWs contaminated with additive white Gaussian noise, it is able to handle both quasi-circular GWs with different mass ratios and eccentric GWs embedded in real LIGO noise. Therefore the proposed method has great generalization performance.

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