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Sandia National Laboratories

Denoising Seismic Signals Using Wavelet-Transform-Based Neural Networks

Powerpoint Slide Version of AGU iPoster virtual poster presentation

Louis Quinone, Rigobert Tibi, Robert Porritt, and Christopher Young

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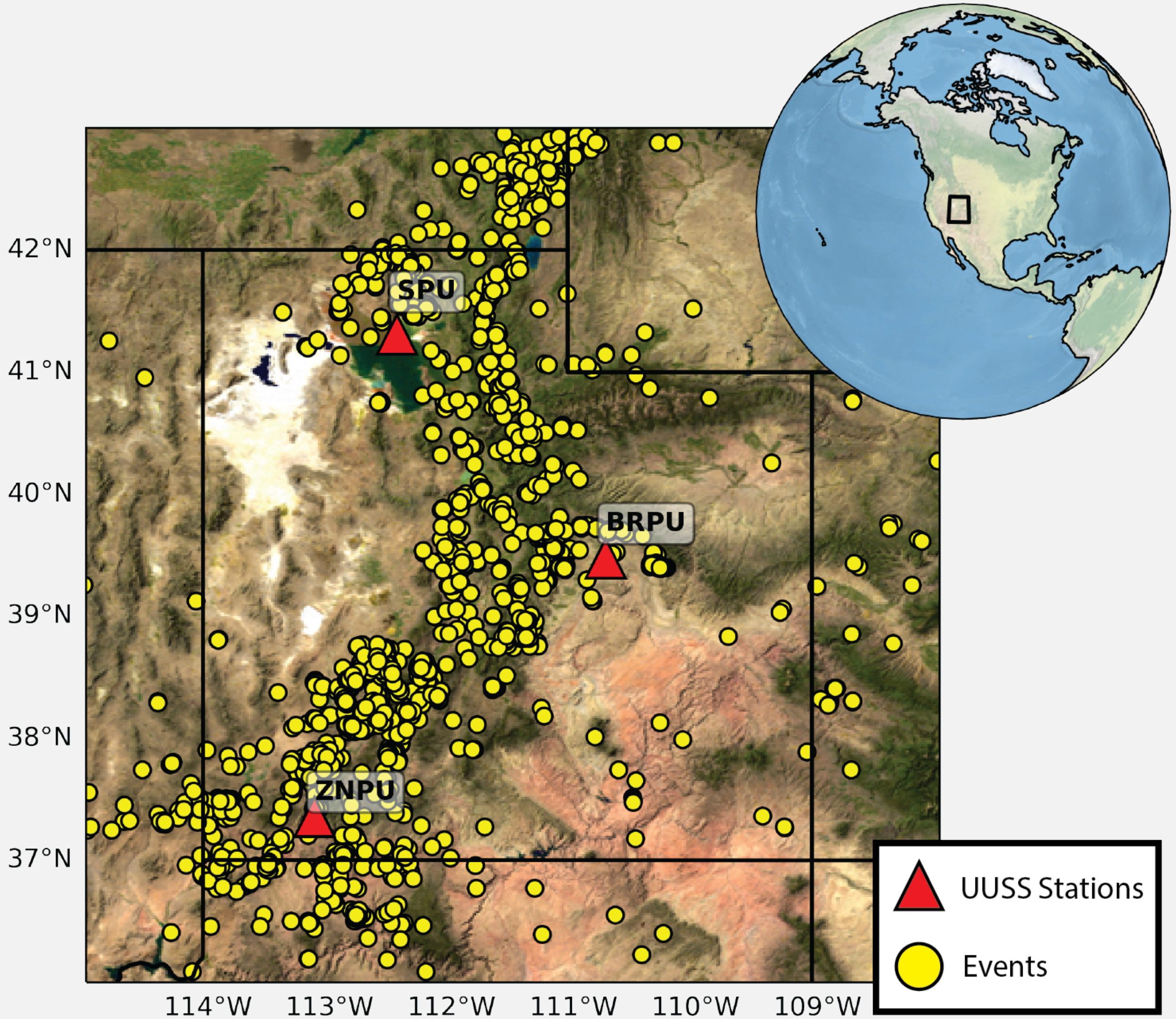
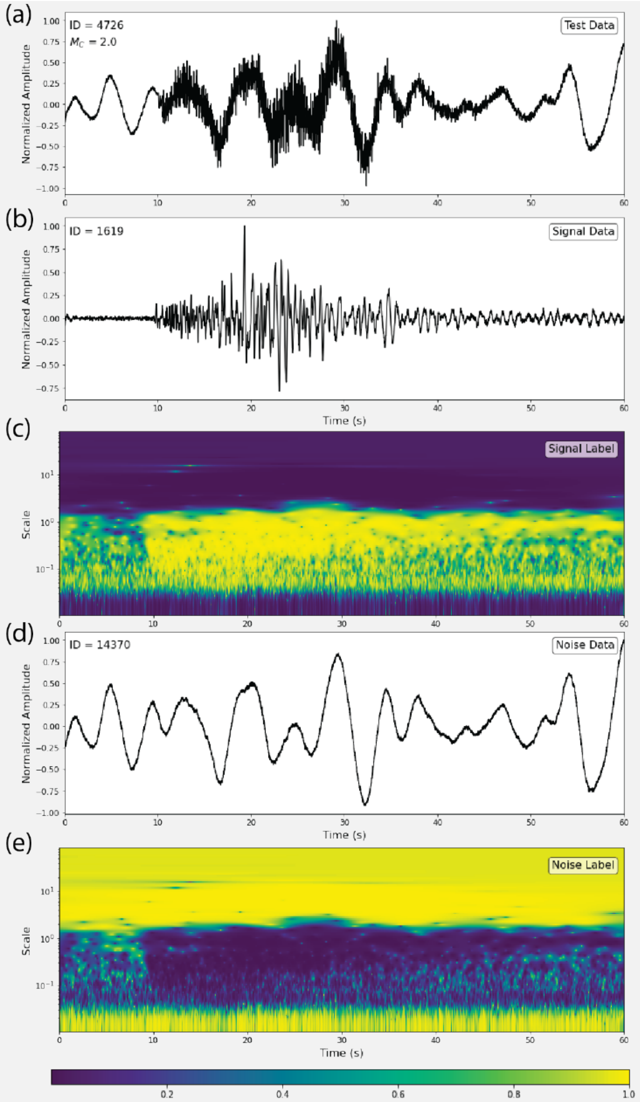
Project Goals



Advancements in the field of image denoising have shown the benefits of incorporating discrete wavelet transforms (DWT) into convolutional neural networks (CNN) to create multi-level wavelet CNN (MWCNN) models.

Using data from the University of Utah Seismograph Stations (UUSS) network we compare the performance of the CNN and MWCNN denoising models using a set of metrics, including correlation coefficients, signal -to-noise ratios, and signal-to-distortion ratios.

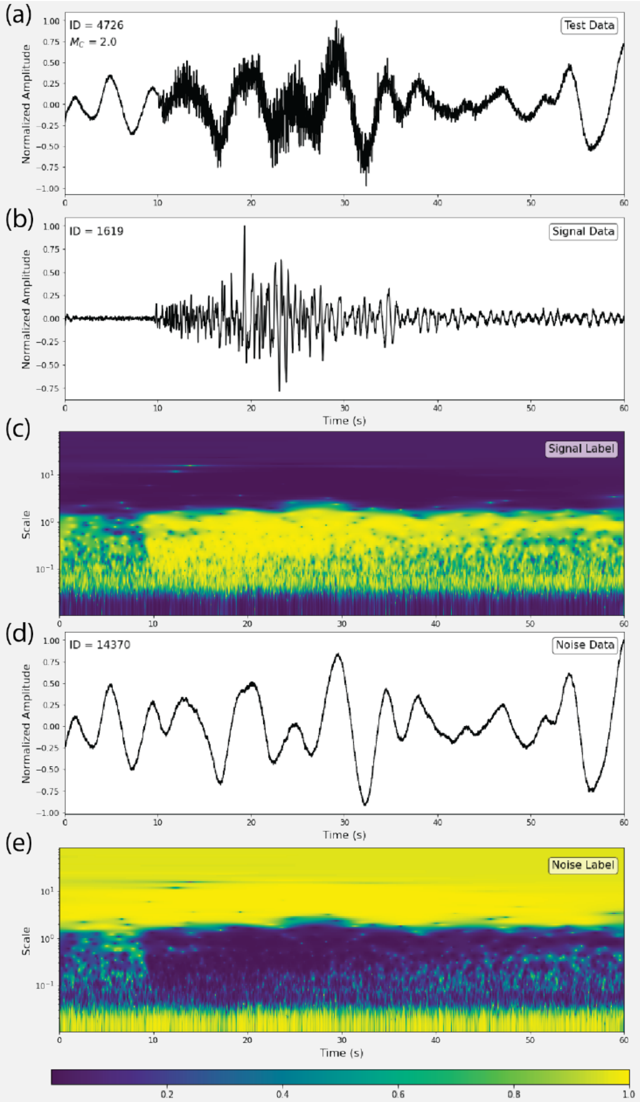
Constructing the Training Data



The training, validation, and test data sets used to train the models were constructed using a set of 3,188 high-SNR "signal" waveforms and 15,426 "noise" waveforms recorded on UUSS stations.

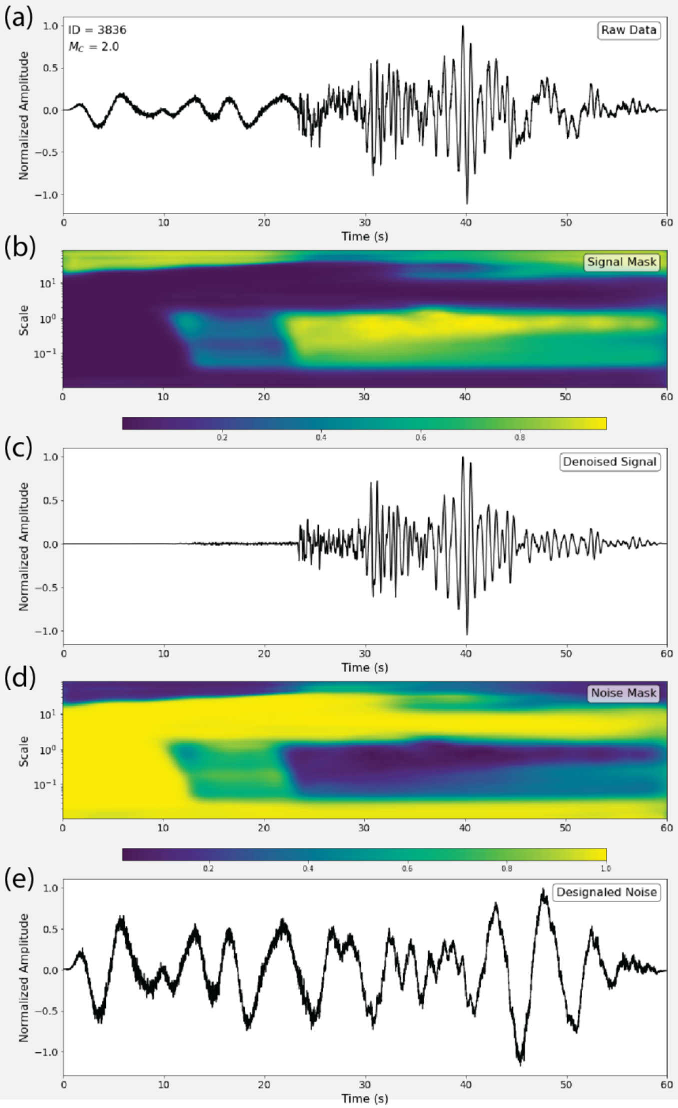
Each of the data sets were constructed by adding each signal waveform with a random noise waveform. This was repeated 60 times to create the total 191,280 waveforms where the signal and noise were pre-separated into sets using a 70-15-15 convention.

Constructing the Training Data



The "noisy waveforms" and each of the original signal and noise waveforms of the training and validation data sets are transformed into the time-frequency domain using the short-time Fourier transform (STFT), or the time-scale domain using the continuous wavelet transform (CWT) method and used as the input and label data for the model training, respectively.

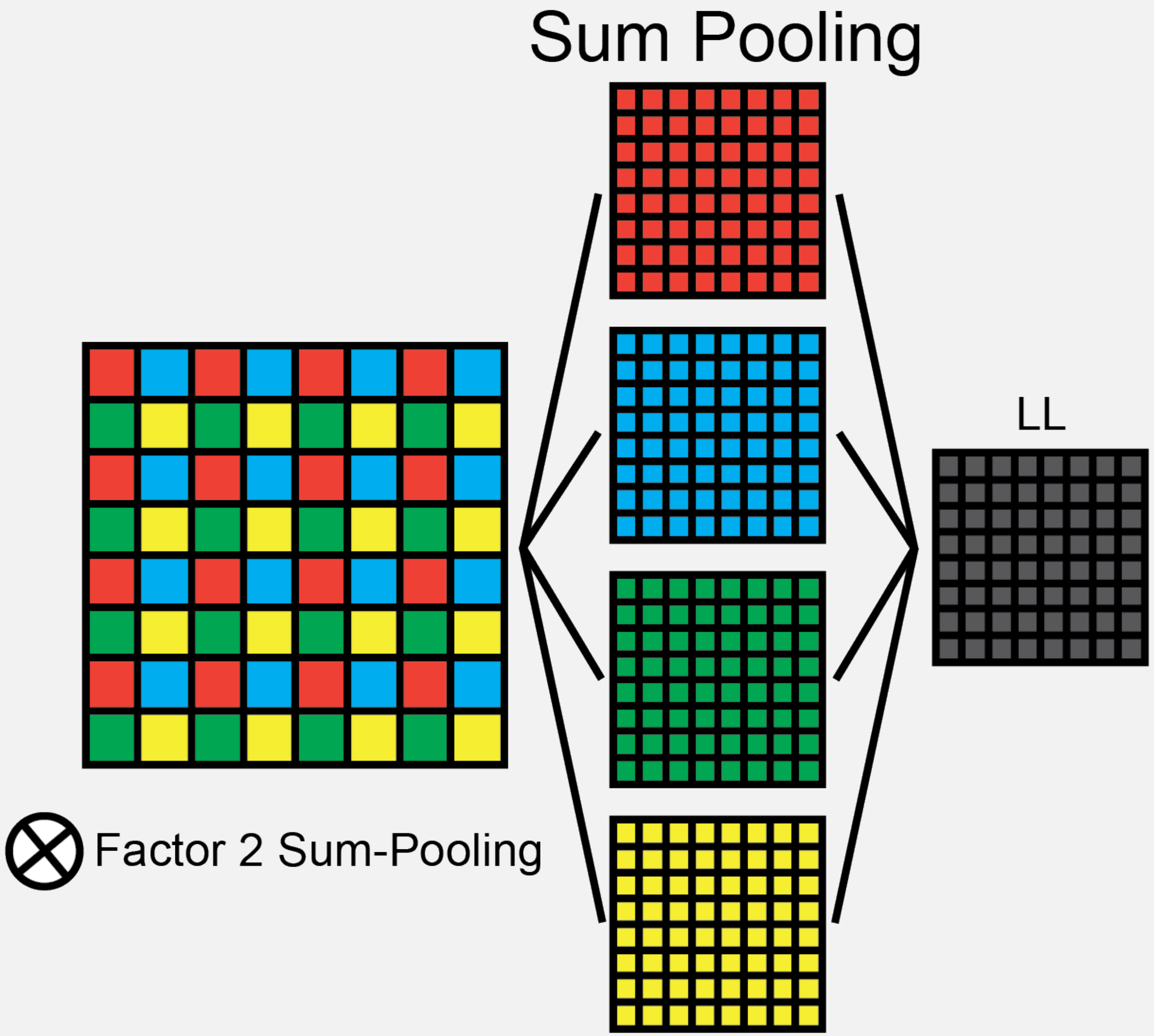
Constructing the Training Data



The denoising models output the signal and noise masks that represent time and frequency-dependent filter operators. When these masks are multiplied with the input waveform and then put through an inverse wavelet transform or STFT operation then the resulting denoised signal and designaled noise waveforms are created.

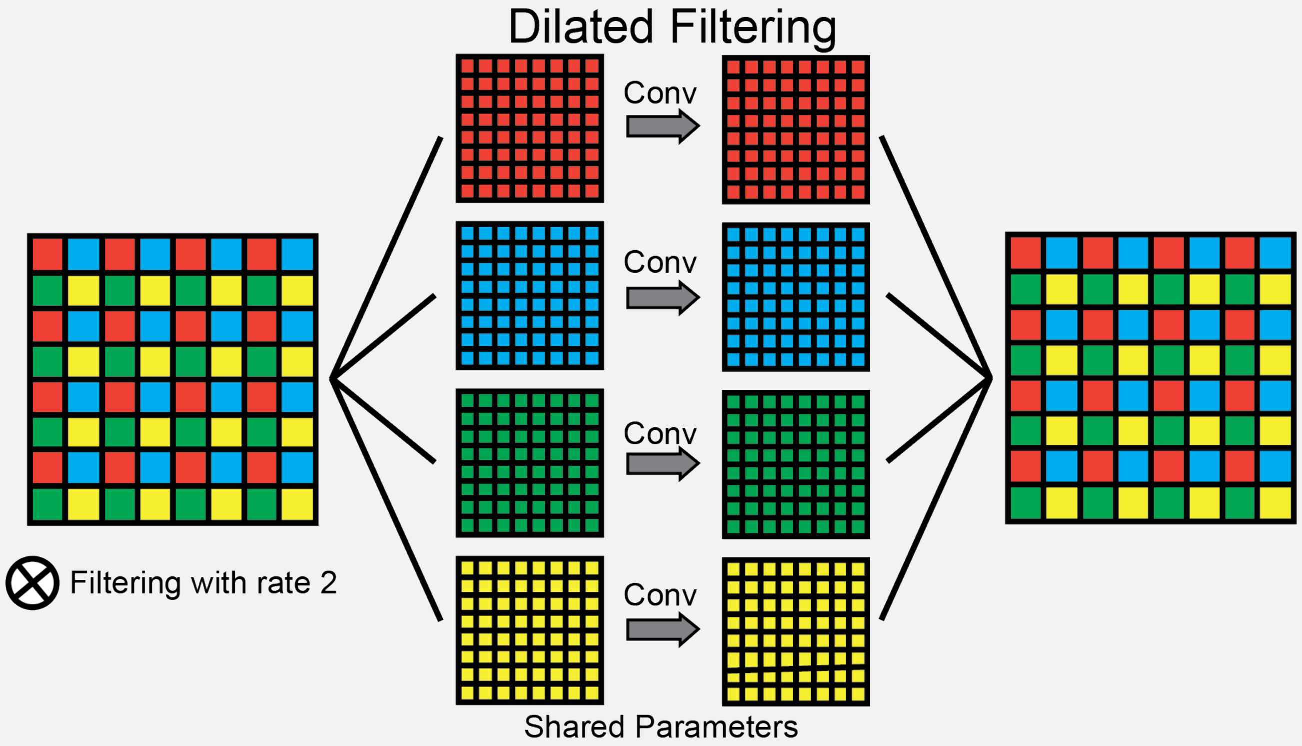
To further evaluate the performance of the model we also gather a set of 5,525 raw 60-sec waveform segments collected on a set of UUSS stations for the period of 2018-2020 containing both earthquake and mining explosion data. The waveform were processed using the denoising approaches.

Wavelet Transforms



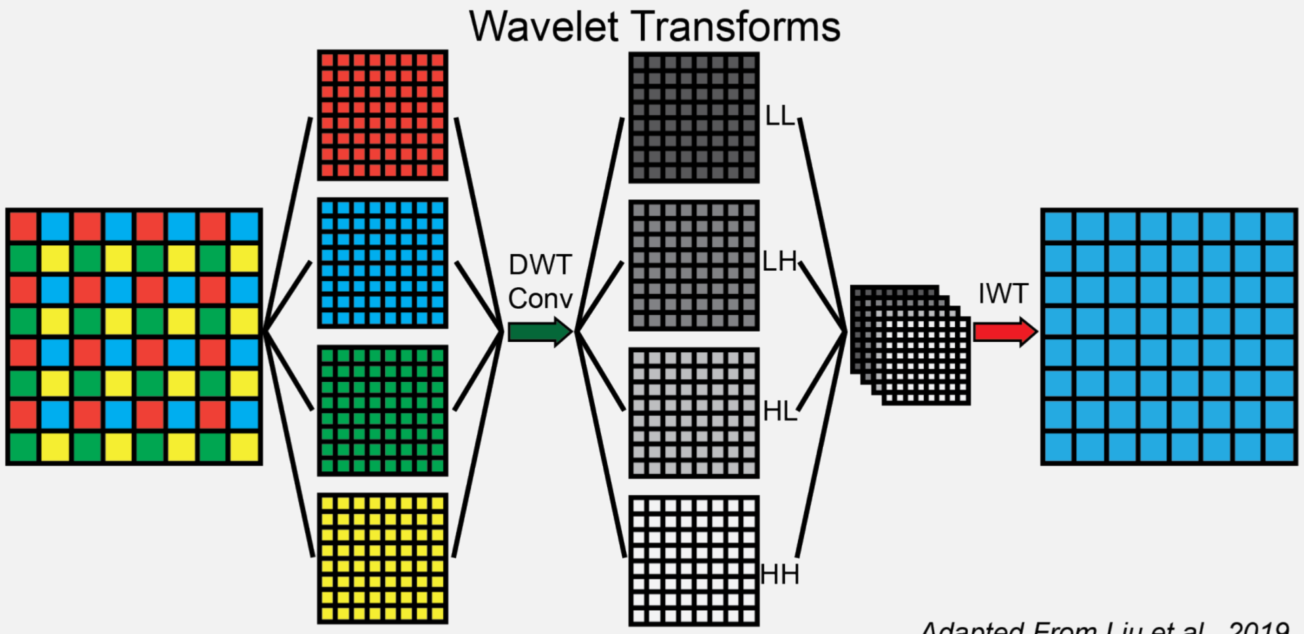
Conventional pooling operations used in convolutional neural networks down-sample an input by using the maximum or average values over a defined window in time-frequency domain, which leads to a loss of all high-frequency data causing poorer processing of feature maps.

Wavelet Transforms



Dilated filtering is a process where a feature map is decomposed into four sub-maps which are then processed through convolution using the same parameters on each sub-map. This operation is usually undertaken in the decoding stage of a U-Net style architecture and is unable to re-construct any data that was previously lost in the encoding stage of the model.

Wavelet Transforms

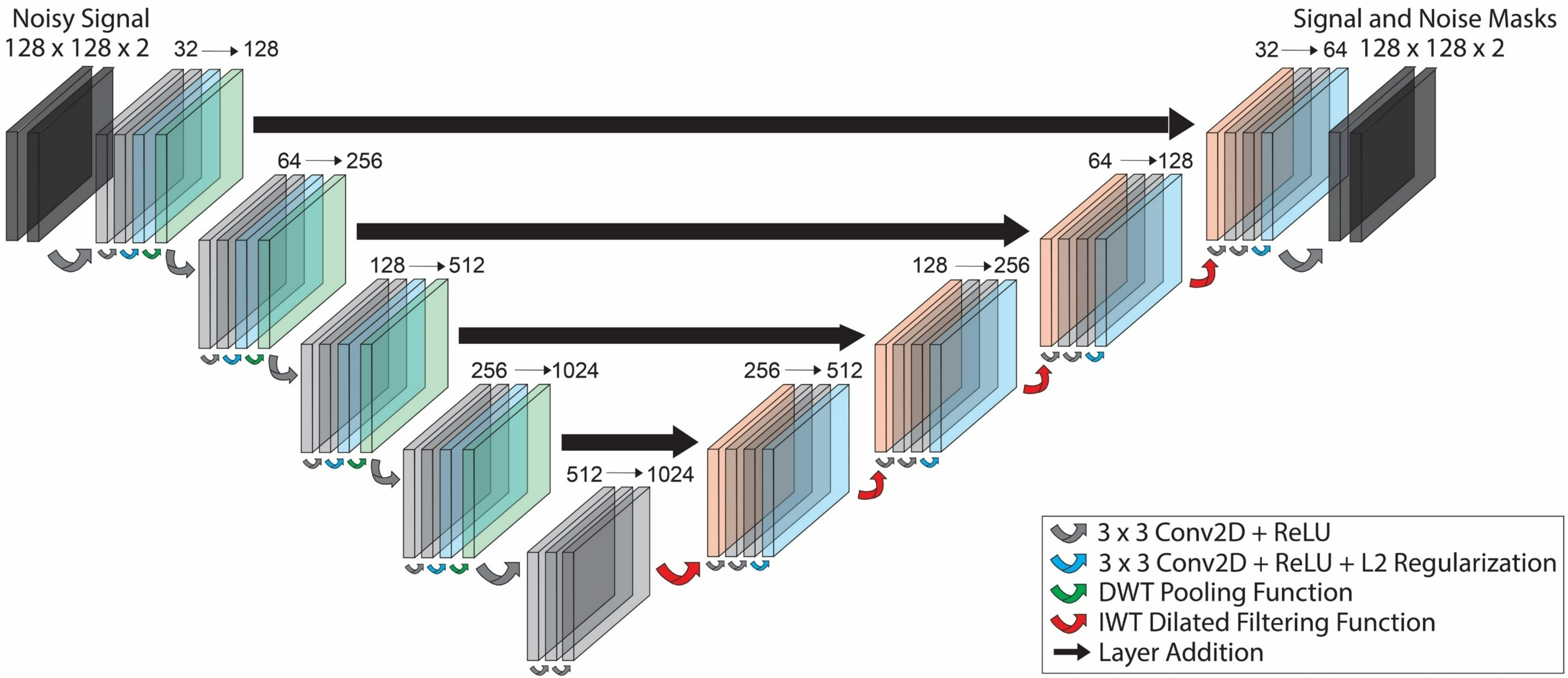


Adapted From Liu et al., 2019

The DWT function is an expanded version of the standard pooling function, wherein we use fixed weights in the convolution process to keep high-frequency data.

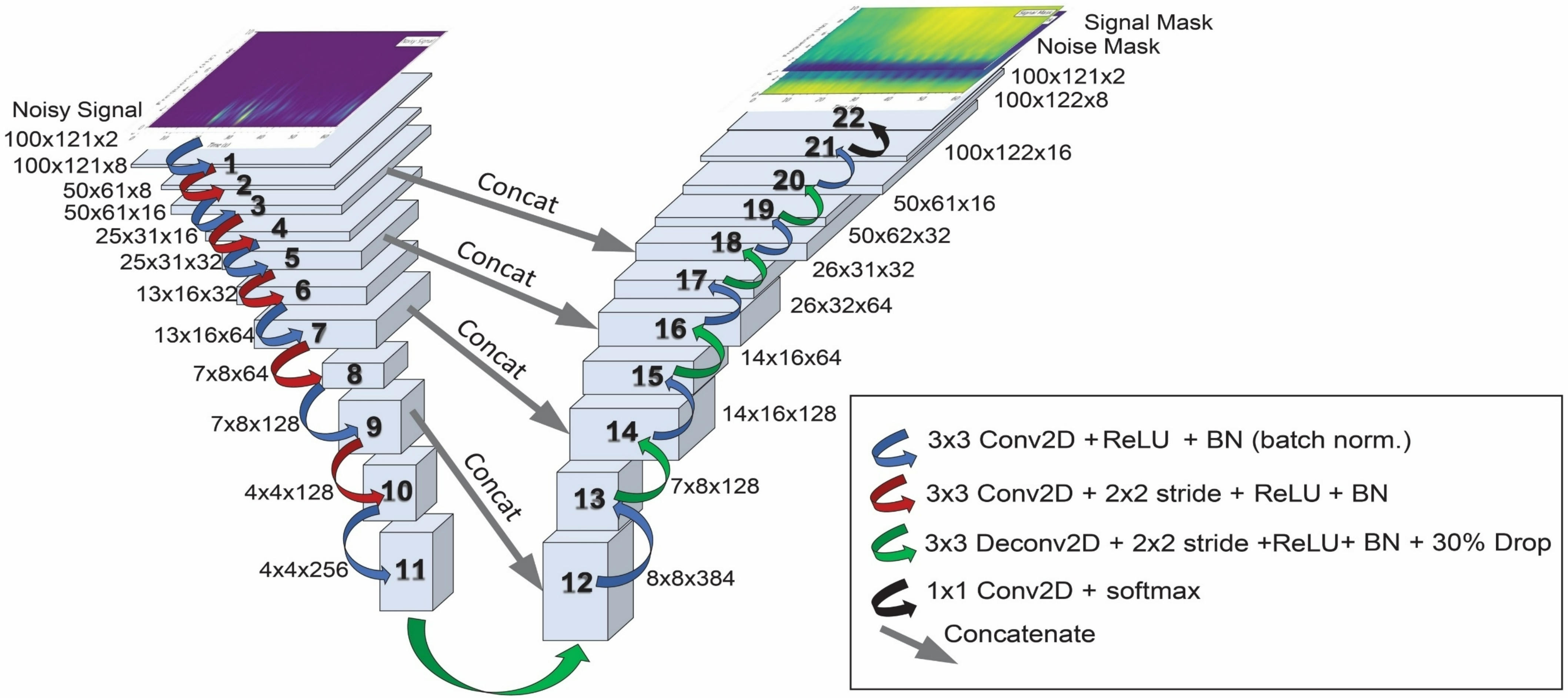
The IWT function reconstructs a feature map from the created sub-images as a type of dilated filtering which doesn't suffer from gridding effects.

MWCNN Model Architecture



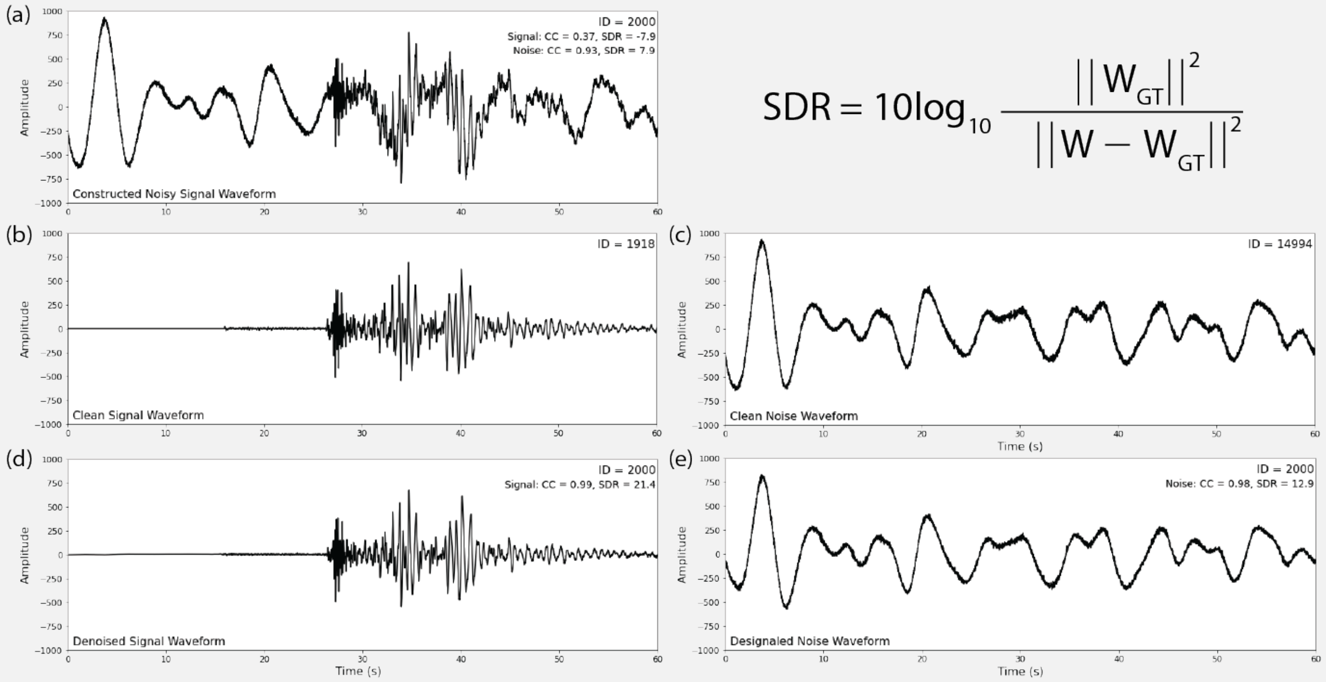
- Architecture of the denoiser network used in the MWCNN version of the model which combines a CNN approach with the use of DWT and IWT to improve image processing performance with each of the boxes representing a different layer with the processes described in the legend.

FCN Model Architecture



• Architecture of the denoiser network that was used in the STFT and CWT-FCN versions of the model which utilizes a fully convolutional model network where each box is a different layer and the legend describe the processes used for each layer. ReLU stands for rectified linear unit.

Model Evaluation Metrics

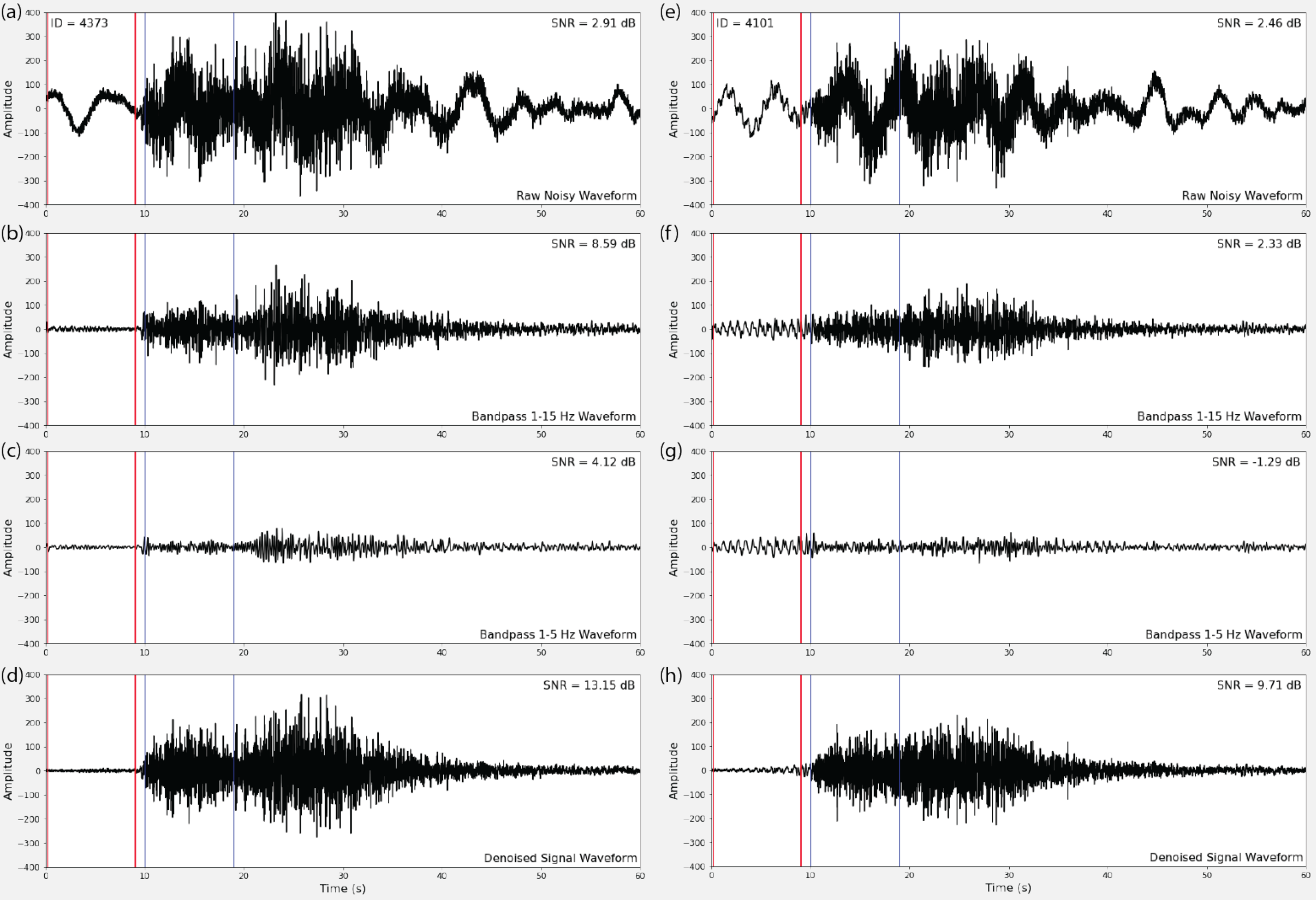


$$SDR = 10\log_{10} \frac{||W_{GT}||^2}{||W - W_{GT}||^2}$$

The models are evaluated using the noise and signal constructed test dataset and a number of different criteria. These criteria include the ability of the denoising model to recover the original signal and noise waveforms with high fidelity. This ability is estimated by measuring the degree of similarity using cross correlation, and the degree of amplitude distortion using the signal-to-distortion ratio (SDR) which we seek to maximize.

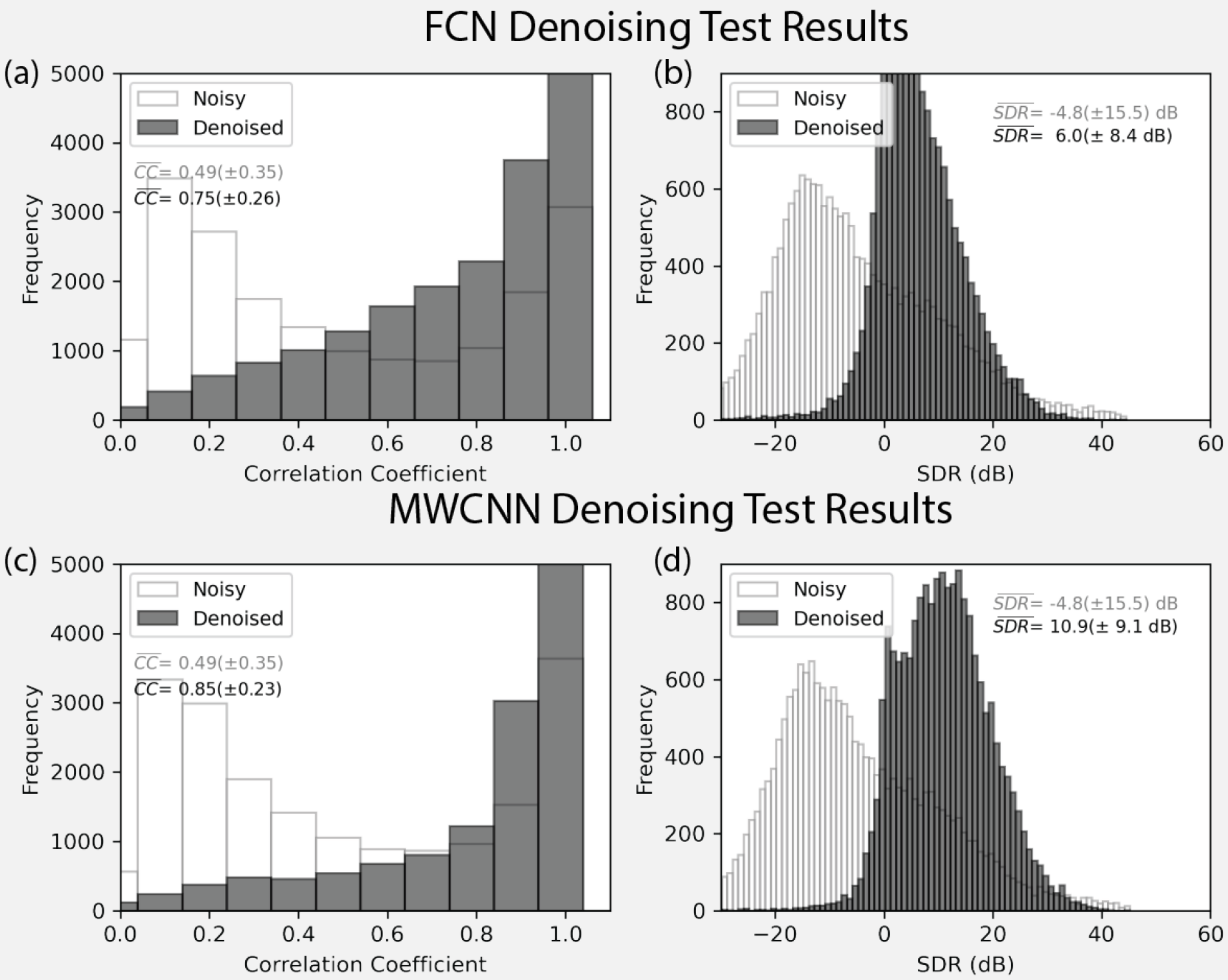
The equation to calculate SDR is shown above with W_{GT} being the original waveforms and W being the recovered (denoised) waveform.

Model Evaluation Metrics



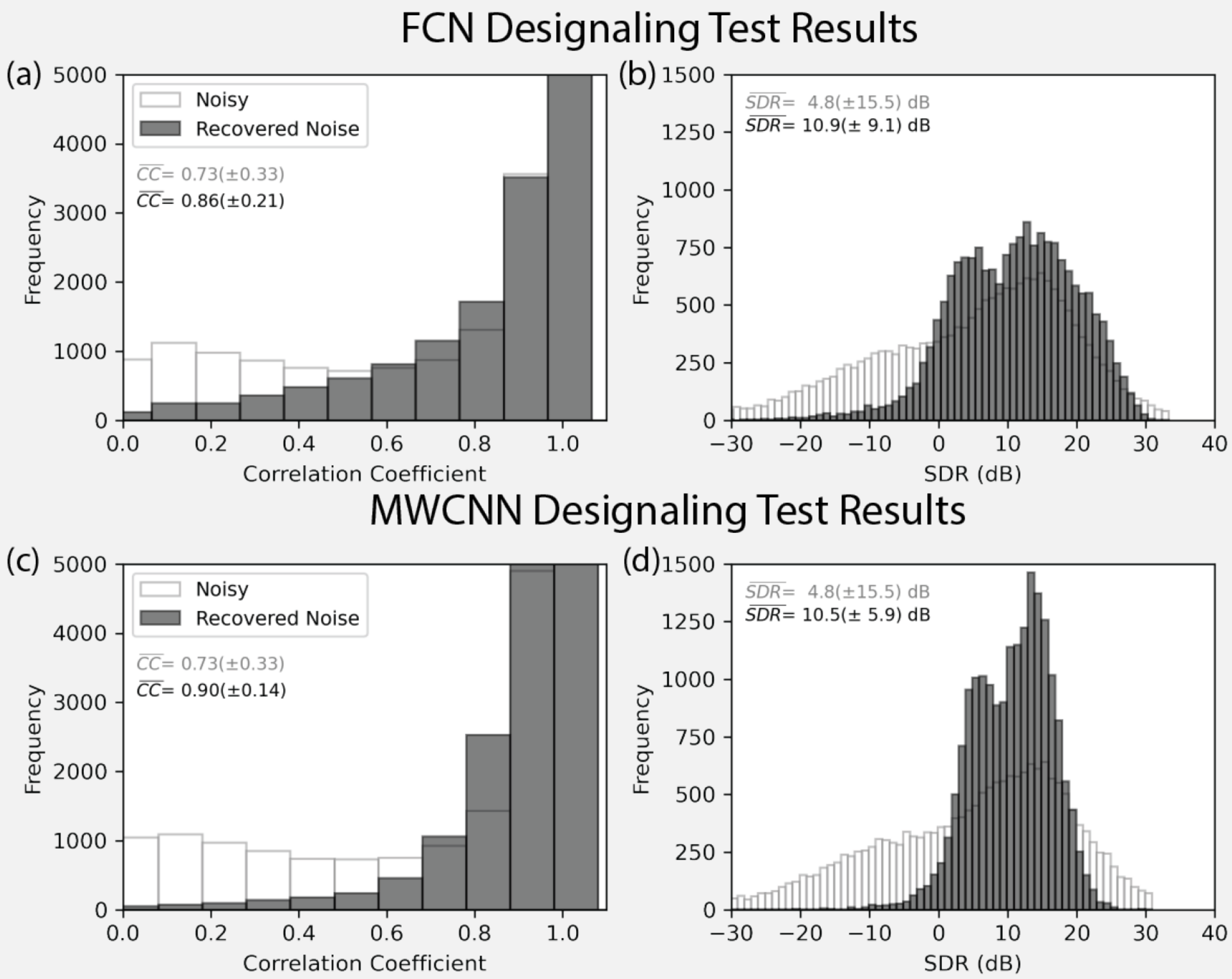
The models are evaluated using real-world non-constructed data collected from selected UUSS network stations where the main evaluation metric is the improvement in SNR of the denoised signal waveforms when compared to the raw waveforms and those that have been bandpass filtered.

Denoising Results



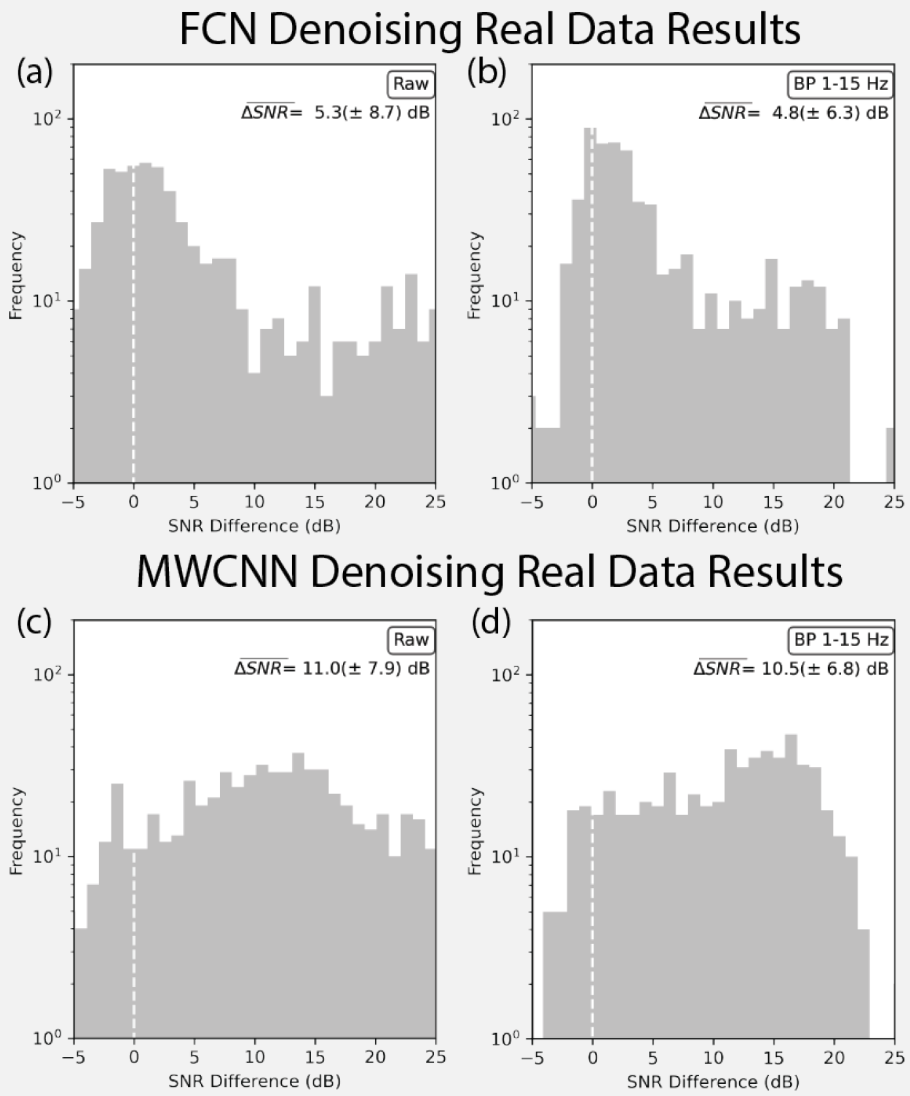
Model evaluation on the test data sets shows that the MWCNN model outperforms the FCN version at being able to re-construct both the shape and amplitude values of the input signal data with higher fidelity.

Denoising Results



The performance of the MWCNN and FCN models is more comparable when it comes to the noise component of the test data. For the test data the MWCNN model was able to slightly improve upon the waveform shape but wasn't able to improve upon the amplitude.

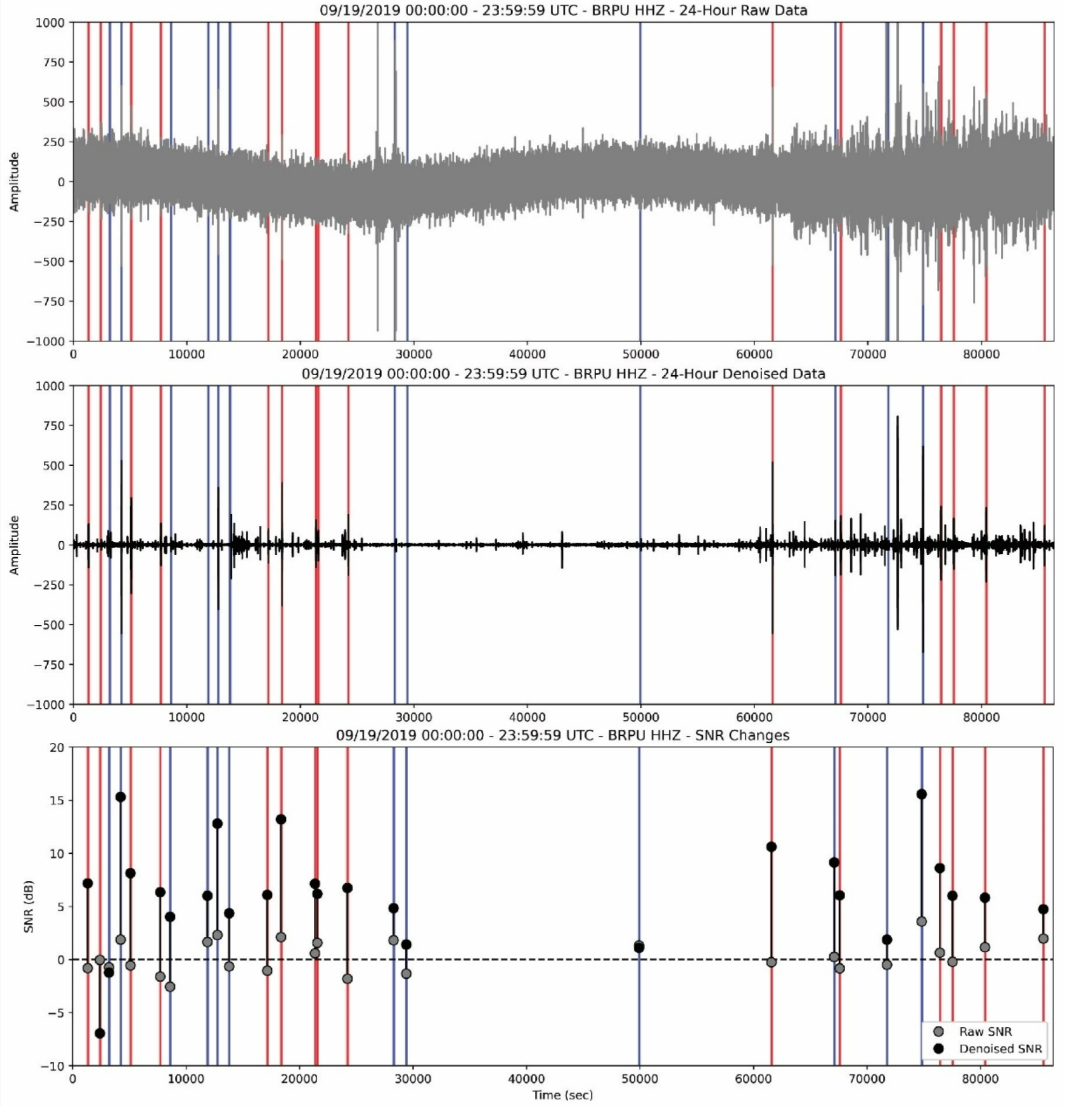
Denoising Results



Comparisons of SNR improvements between each of the denoising models and bandpass filtering show that the denoisers consistently outperform standard bandpass frequency filtering.

The MWCNN model greatly outperforms the FCN denoising model where the distribution of SNR improvements are more evenly distributed across greater values.

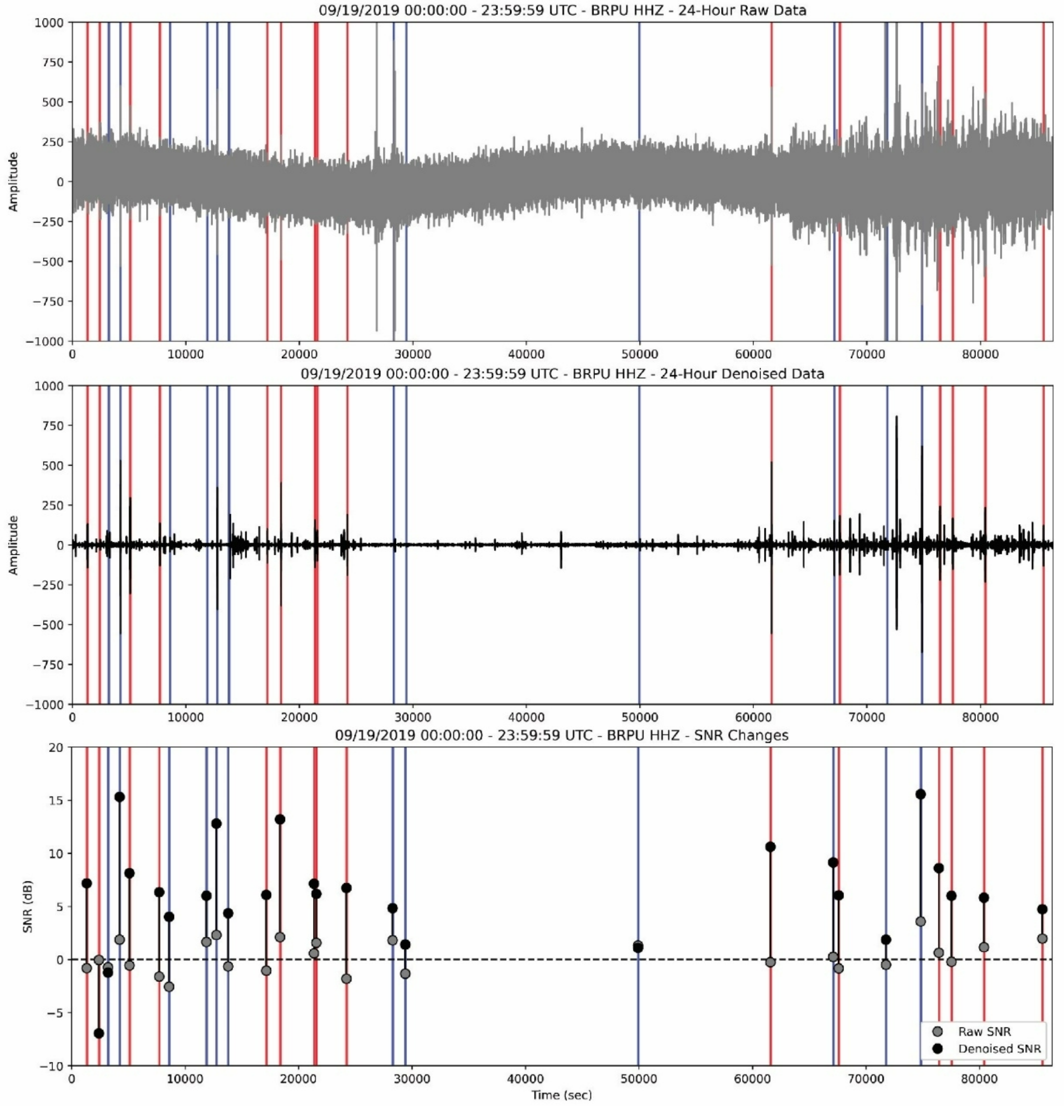
Application to Continuous Data



We examine the ability of the MWCNN model to denoise continuous data by examining a 24-hour period on the vertical channel of station BRPU where there had previously been 12 detected events (shown above as blue vertical bars).

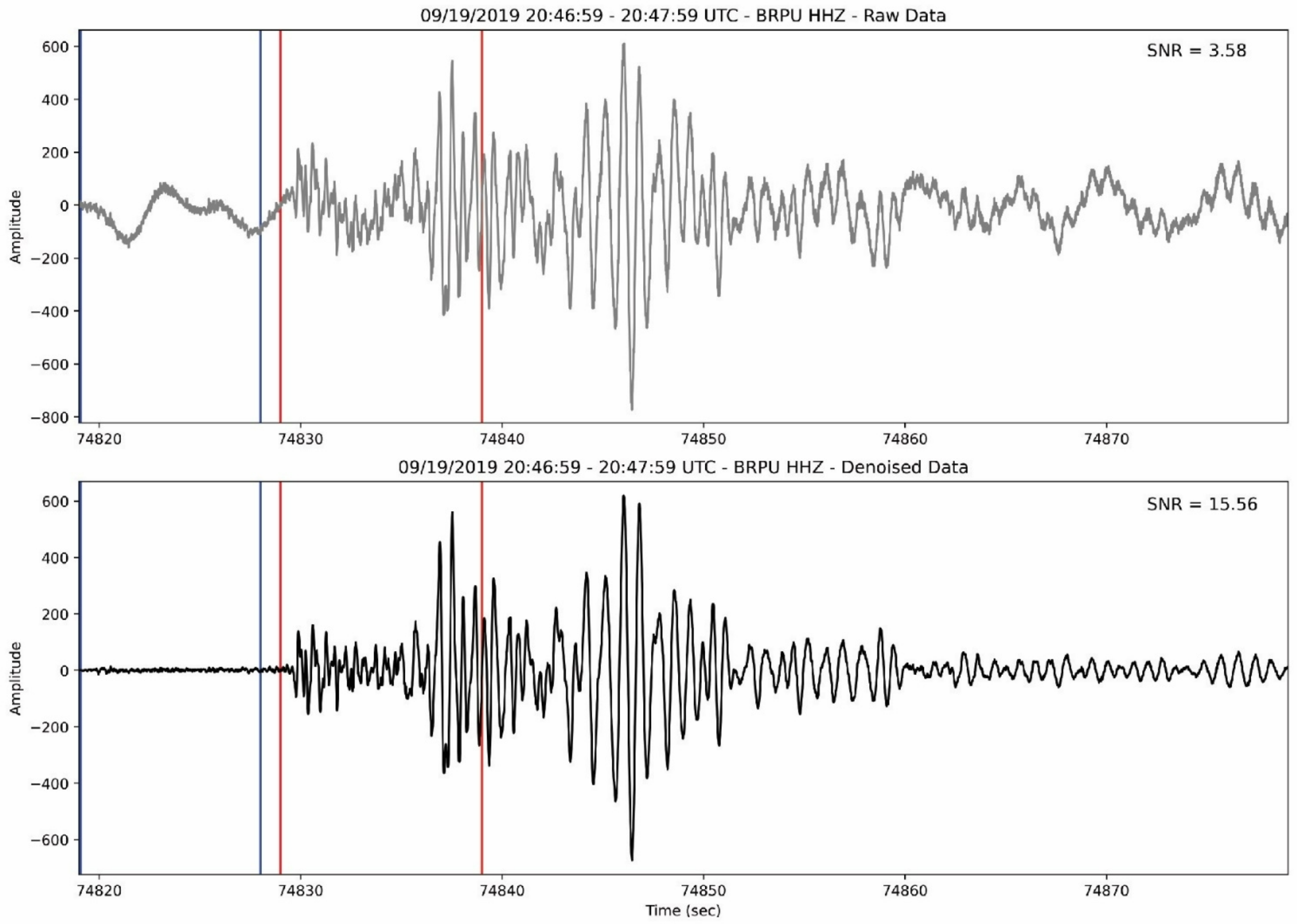
To examine the potential of the MWCNN denoiser to help improve detection capabilities we ran an STA/LTA detector on the same segment of 24-hour data and found an additional 15 event detections (shown above as red vertical bars).

Application to Continuous Data



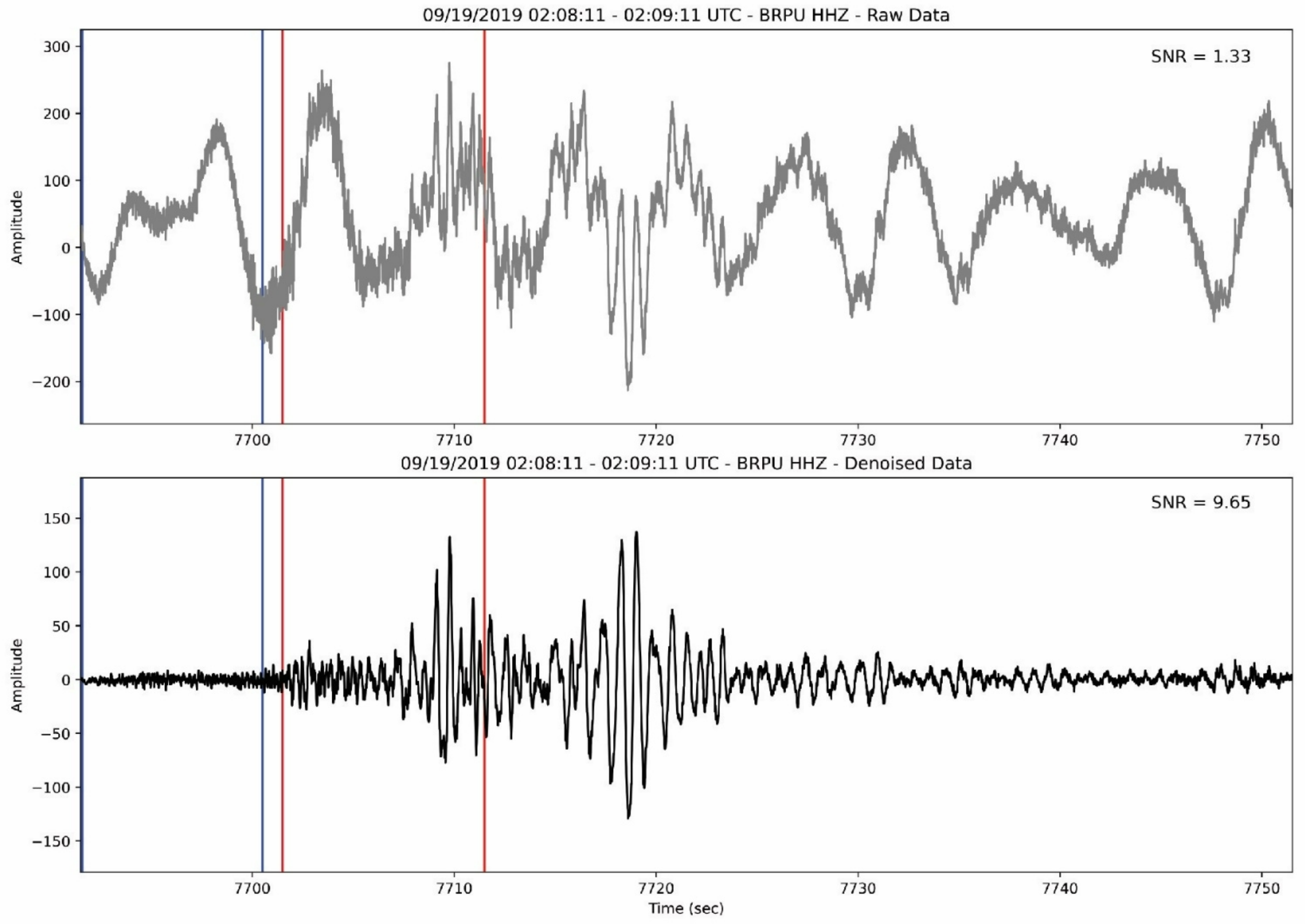
We examine the SNR differences between the raw and denoised data for both the original (blue) and newly detected (red) events and find that the denoiser consistently improves SNR values of detected events.

Application to Continuous Data



Here, we show an example of an event that was able to be detected from the raw data and show how the MWCNN denoiser can improve the event's SNR. The event SNR is calculated by examining a 10-second signal window (bounded by red lines) and a preceding 9-second noise window (bounded by blue lines).

Application to Continuous Data



Here, we show an example of an event that wasn't detected on the raw data but becomes much clearer using the denoised data.

Ultimately, we conclude that the MWCNN denoising model can greatly improve event detection capabilities and can either be utilized to re-analyze previously detected events or to search for potential missed events in segments of continuous data.

Disclosures

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