Denoising Seismic Signals Using Wavelet-Transform-Based Neural Networks

Louis Quinones[1], Rigobert Tibi[1], Robert Porritt[1], and Christopher Young[1]

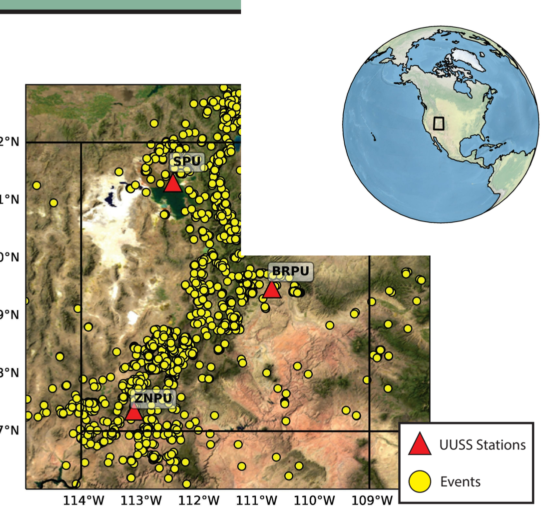
[1]Sandia National Laboratories

Sandia National Laboratories

SSA Seismological Society of America

2022 Annual Meeting

Project Goals



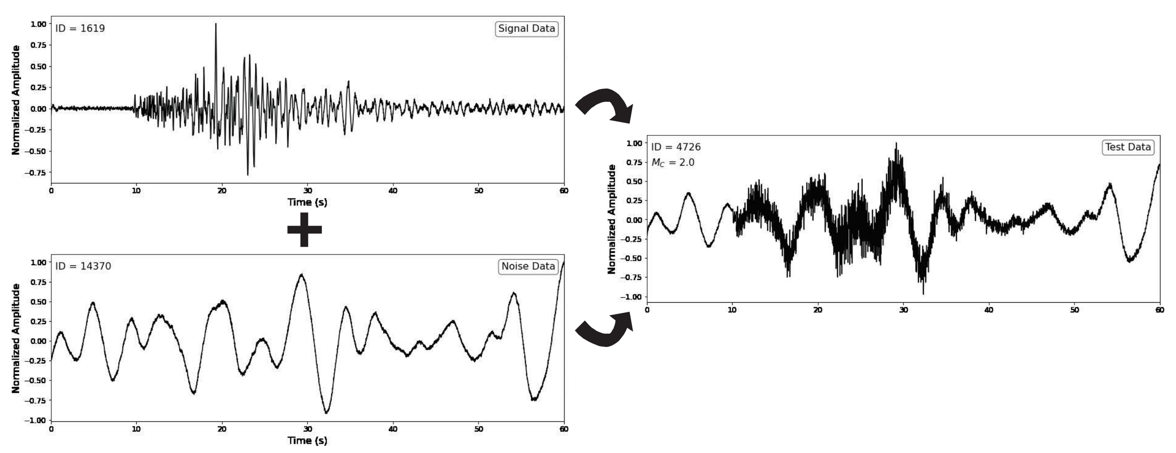
• Advancements in the field of image denoising have shown the benefits of incorporating discrete wavelet transforms (DWT) into convolutional neural networks (CNN) to create multi-level wavelet CNN (MWCNN) models.

• Using data from the University of Utah Seismograph Stations (UUSS) network we compare the performance of the CNN and MWCNN denoising models using evaluation metrics such as: cross-correlation, and amplitude distortion, and signal-to-noise ratios (SNR) improvements of real-world data.

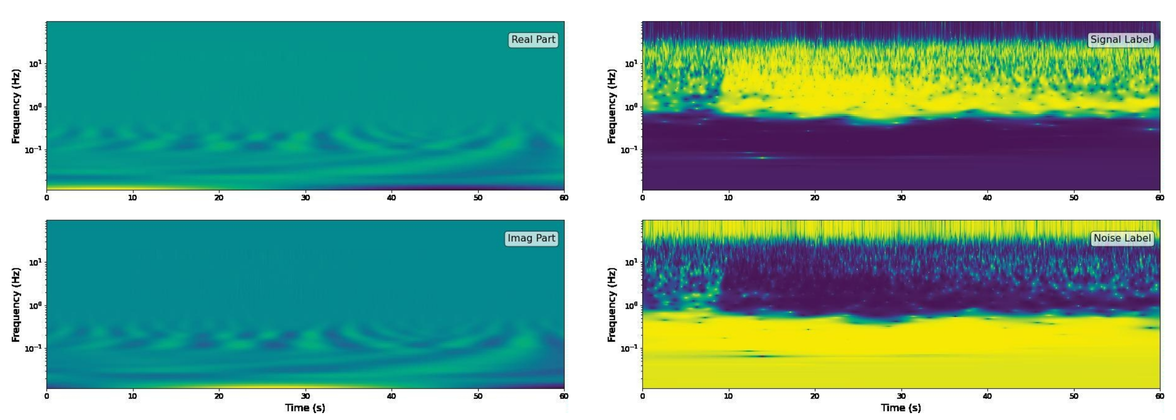
Creation of Training Data

• The training, validation, and test data sets used to train and evaluate 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 40 times to create the total 127,520 waveforms where the signal and noise were pre-separated into sets using a 70-15-15 convention

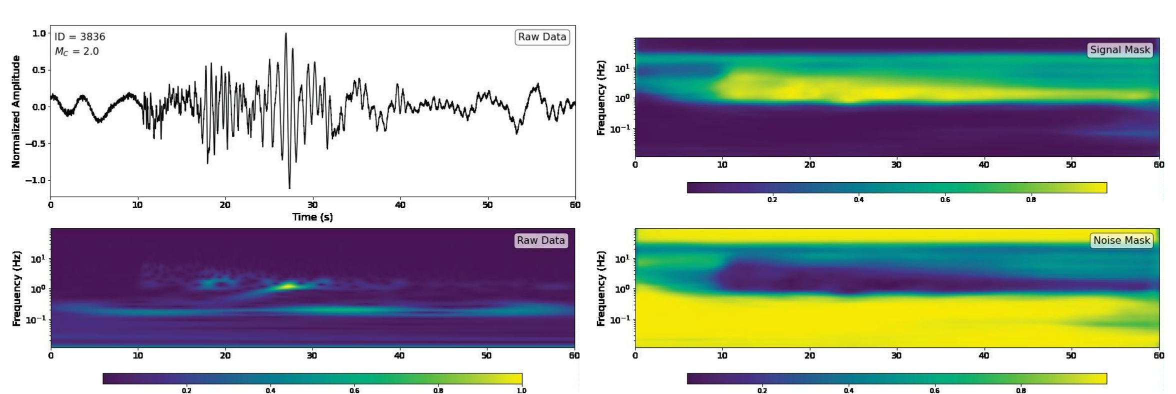


• The "noisy waveforms" and each of the original signal and noise waveforms of the training and validation data sets are transformed into the time-frequency domain using the short-time Fourier transform (STFT), or the time-scale domain using the continuous wavelet transform (CWT) method and used as the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



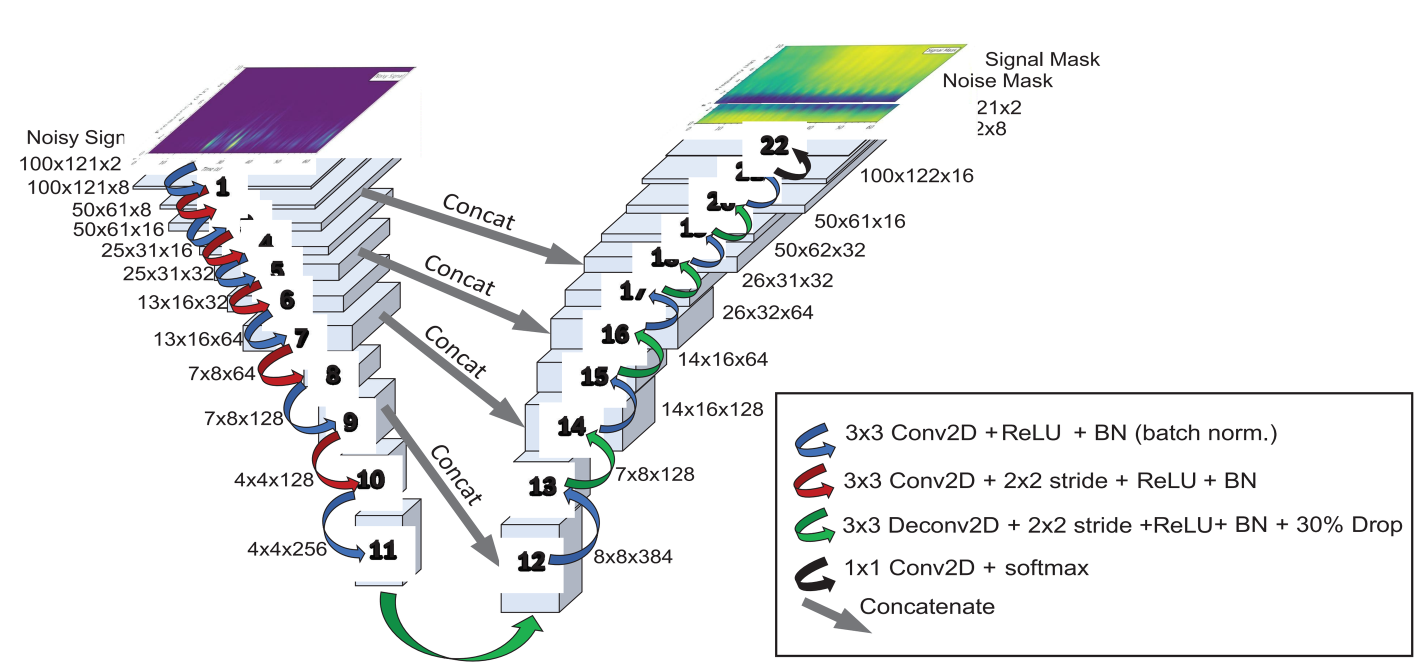
• To further evaluate the performance of the model we also gather a set of 5,525 raw 60-sec waveform segments collected on a set of UUSS stations active from 2009-2017 containing both earthquake and mining explosion data. The waveform were processed using the denoising approaches.

• The denoising models provide the signal and noise masks that represent time-dependent filter operators. Examples of those masks are shown below.



Network Architectures

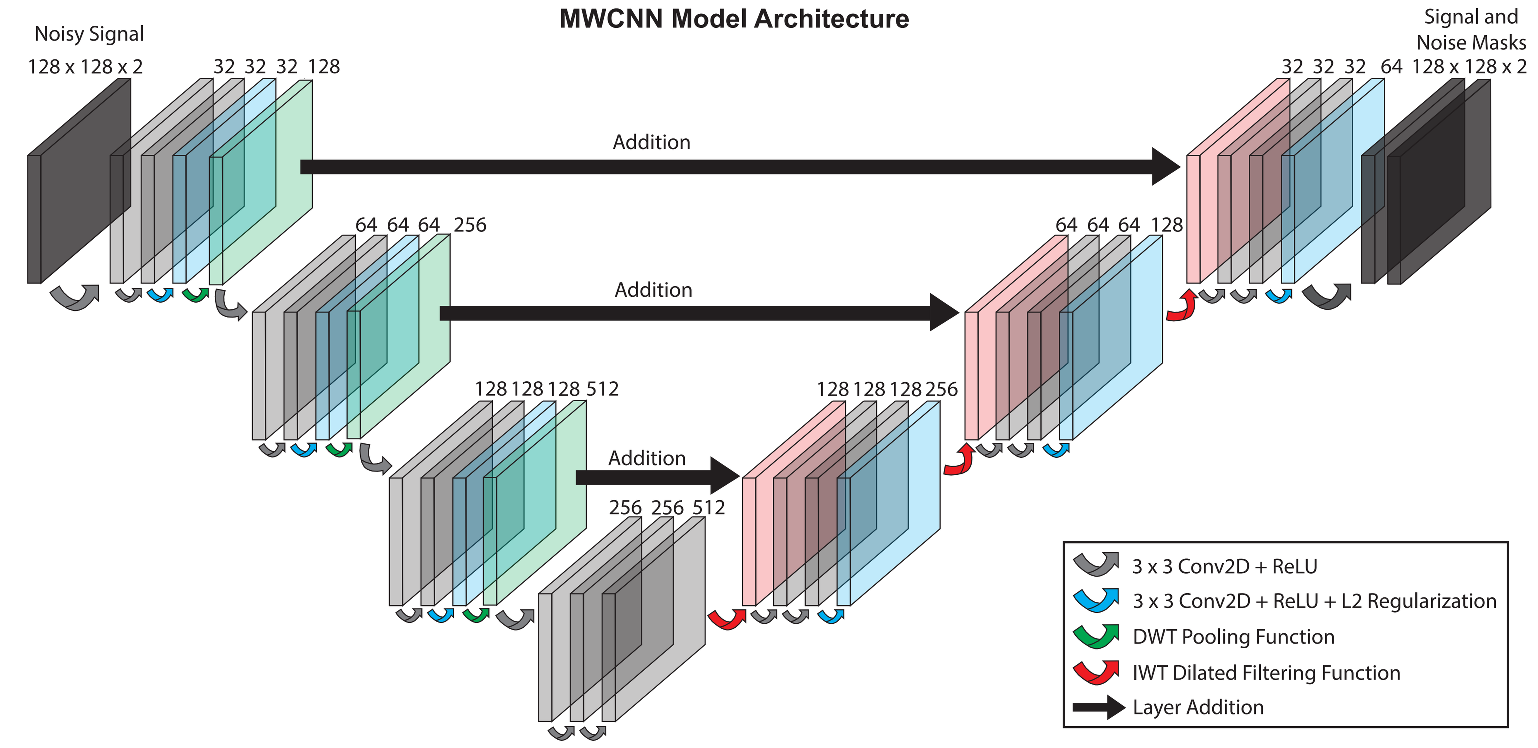
STFT and CWT-FCN Model Architecture



Source: Tibi et al., 2021

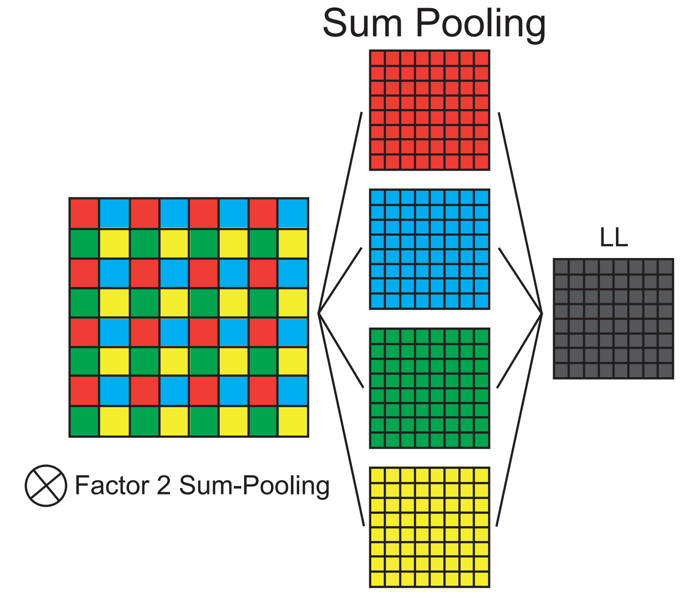
• Architecture of the fully convolutional network (FCN) used to build the STFT and CWT FCN versions of the model. Each box in the network represents a layer; and the processes taking place in each layer are described in the legend. ReLU stands for rectified linear unit.

MWCNN Model Architecture



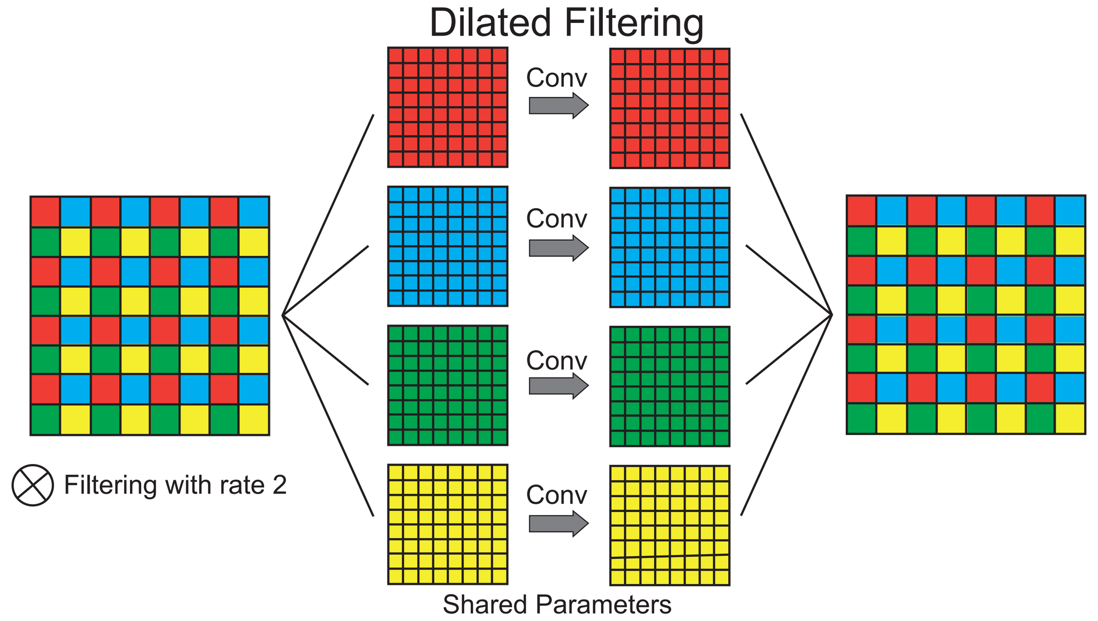
• Architecture of the denoiser network used in the MWCNN version of the model, which combines a CNN approach with DWT and inverse wavelet transforms (IWT). Each box represents a layer; and processes taking place in each layer are described in the legend.

Sum Pooling



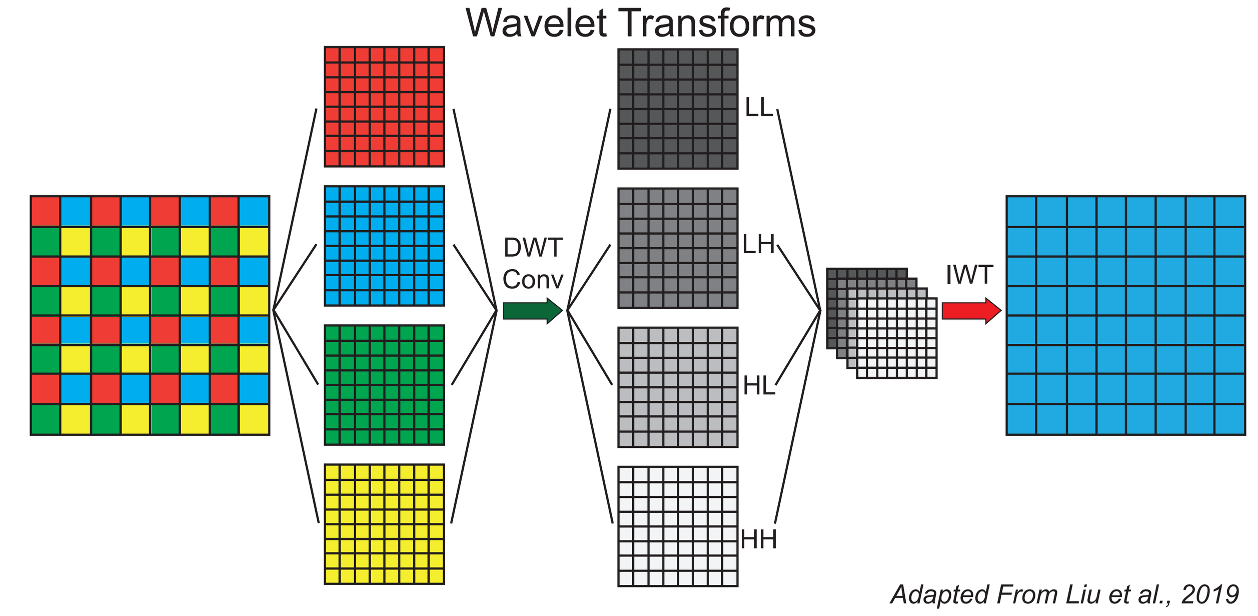
• The conventional pooling operation which down-samples an input by using the maximum or average values over a defined window leads to a loss of all high-frequency data causing poorer processing of feature maps.

Dilated Filtering



• 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.

Wavelet Transforms

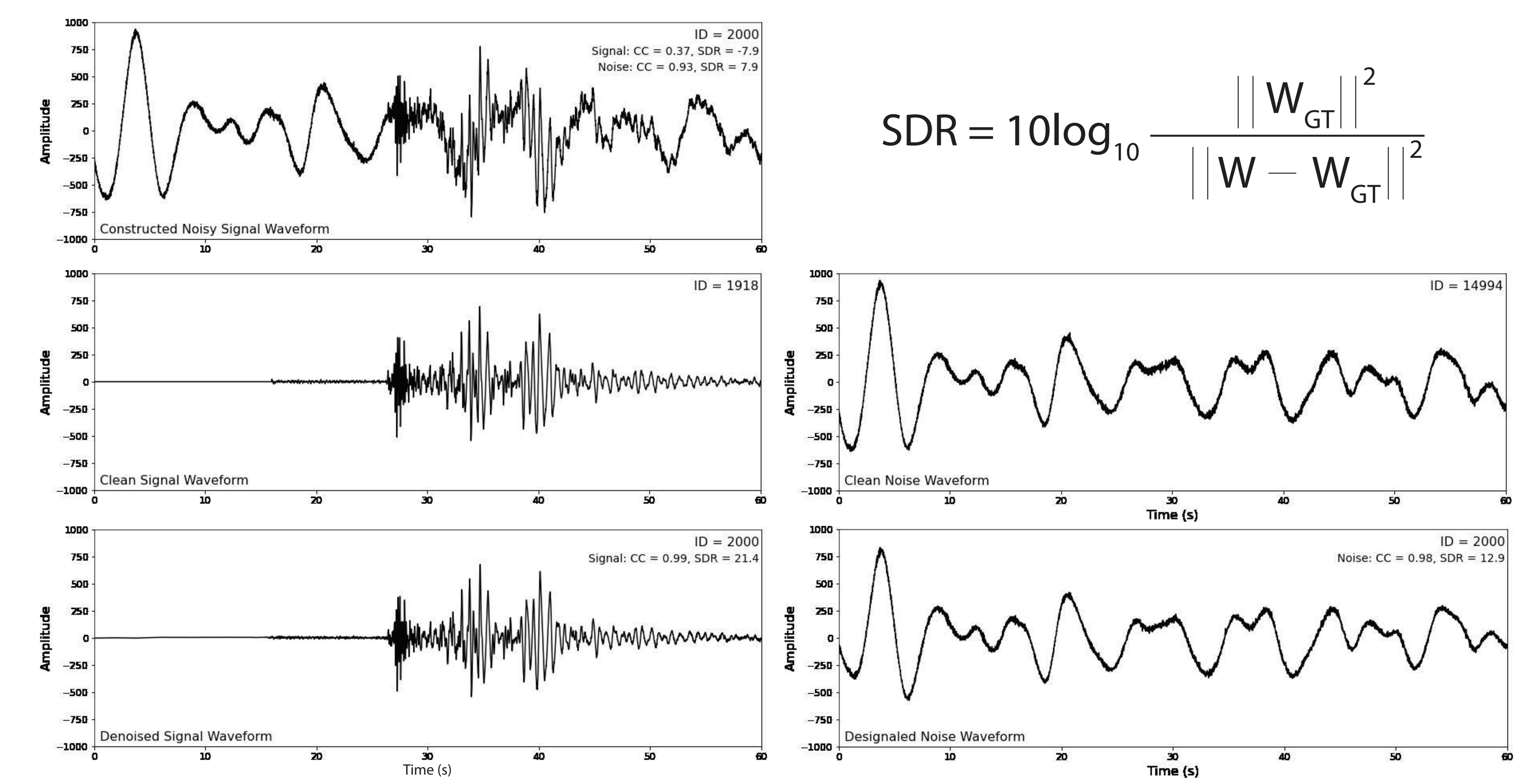


Adapted From Liu et al., 2019

• 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.

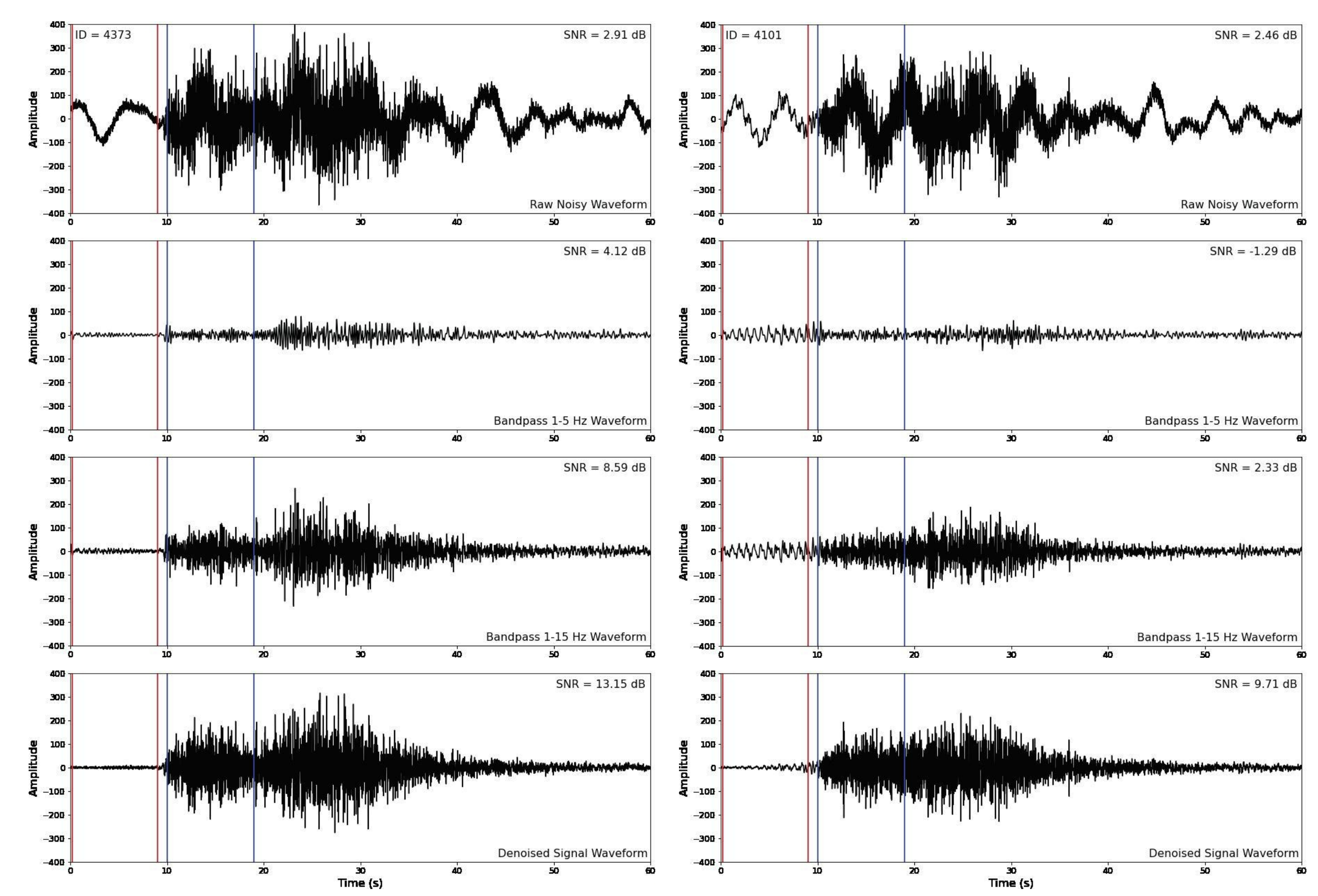
Model Evaluation



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

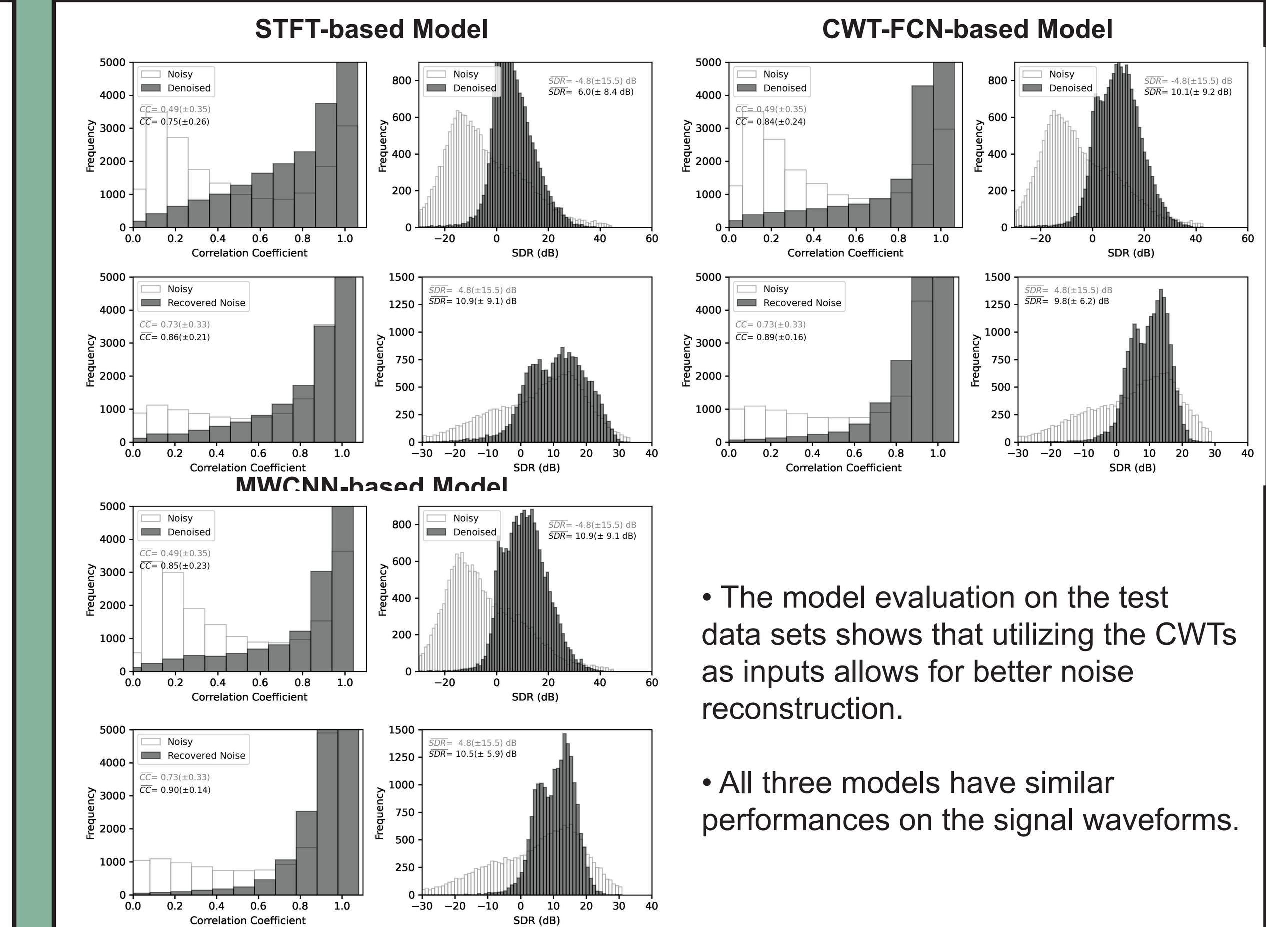
• The models are evaluated using the noise and signal constructed test dataset and a number of different criteria, including the ability of the denoising model to recover the original signal and noise waveforms. This ability is estimated by measuring the degree of similarity using cross correlation, 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 reconstructed waveform.



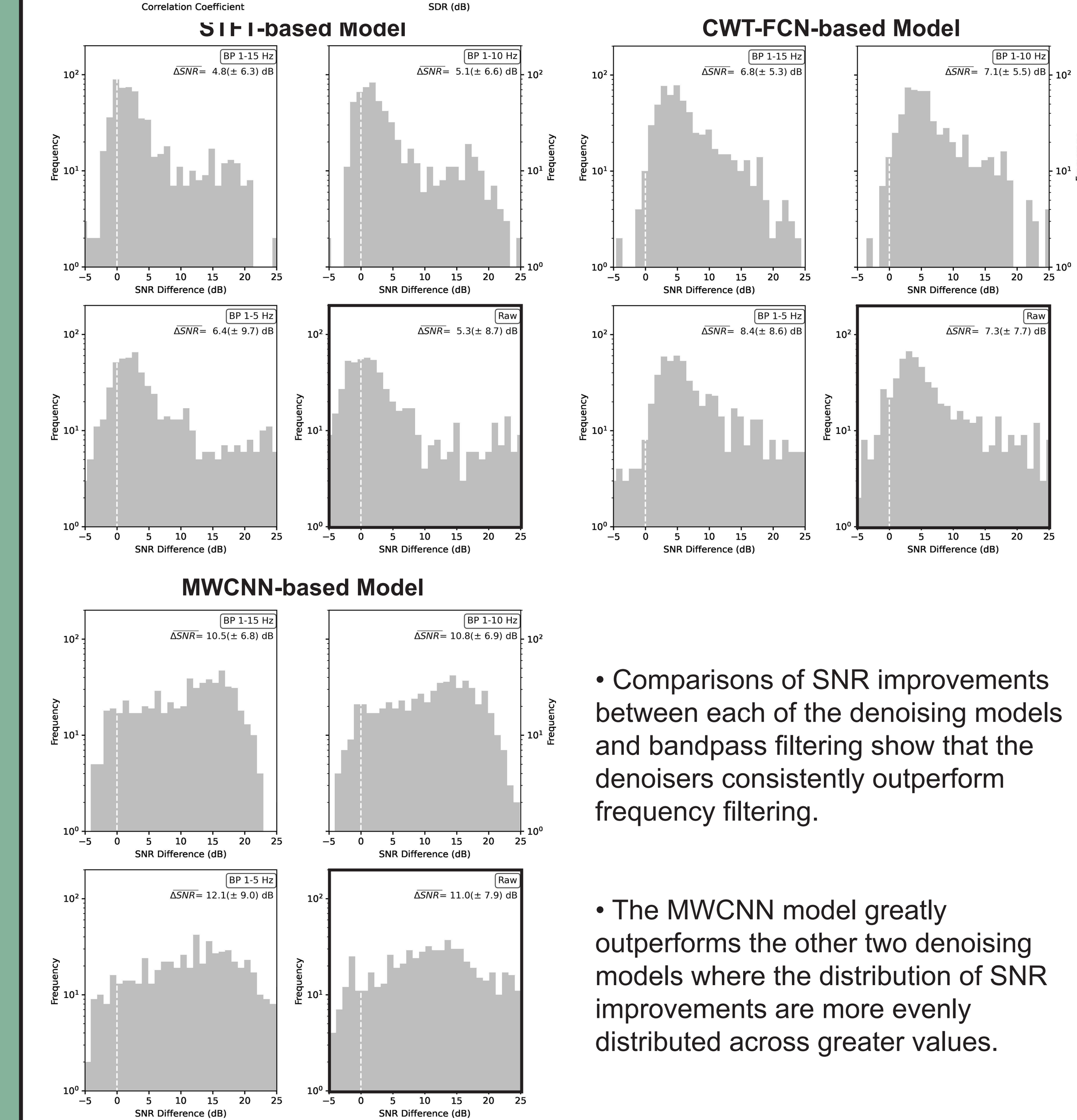
• The models evaluate real-world non-constructed data collected from selected UUSS network stations where the main evaluation metric is the improvement in SNR of the denoised signal waveforms when compared to the raw waveforms and those that have been bandpass filtered.

Denoising Results



• The model evaluation on the test data sets shows that utilizing the CWTs as inputs allows for better noise reconstruction.

• All three models have similar performances on the signal waveforms.



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

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

Conclusions and Future Work

• Three denoising models were built using the same training data set. Evaluation of the models suggests that the incorporation of DWT and IWT greatly improves performance on real word data.

• Currently, the model are designed for predefined segments of data; but, our intent is to transition to processing continuous data.

• Portability of the MWCNN model to regions outside the UUSS network remains a key question to be examined.

This research was funded by the U.S. Department of Energy. Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA-0003525. The views expressed in the article do not necessarily represent the views of the U.S. Department of Energy or the United States Government. This research was funded by the National Nuclear Security Administration, Defense Nuclear Nonproliferation Research and Development (NNSA DNN R&D). The authors acknowledge important interdisciplinary collaboration with scientists and engineers from LANL, LLNL, MSTS, PNNL, and SNL.

Tibi, R., P. Hammond, R. Brogan, C. J. Young, and K. Koper (2021). Deep Learning Denoising Applied to Regional Distance Seismic Data in Utah, Bull. Seismol. Soc. Am. 111, 775–790, doi: 10.1785/0120200292

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