Seismic Signal and Noise Separation Using Deep Neural Network on Downhole Distributed Acoustic Sensing Array Records at SAFOD

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Abstract

Distributed Acoustic Sensing (DAS) is an emerging technology that is promising in monitoring earthquakes with low cost per sensor. We implemented neural networks to denoise the 2D DAS earthquake recordings. We experimented two architectures: U-Net based models and Xception. The neural networks were trained on synthetic data and evaluated on field data. And we chose Unet1 as our best model. Using signal-to-noise ratio (SNR) as a denoising metric, we found that Unet1 performs better than the wavelet baseline model in all of the five randomly chosen validation and field data.

Dataset & Features

Field Data

- 800 × 2000 2D grey scale images
- Distributed Acoustic Sensing (DAS) recording

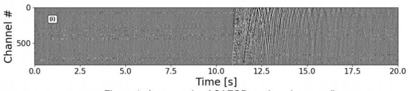

Figure 1: An example of SAFOD earthquake recordings

Synthetic DAS Data

- 800 × 2000 2D grey scale images
- 20s recordings
- Train / Validation / Test samples : 1500 / 140 / 140
- Preprocessing: STFT and normalized by L2-norm

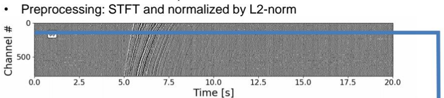

Figure 2: An example of the synthetic DAS data using one of the geophone data

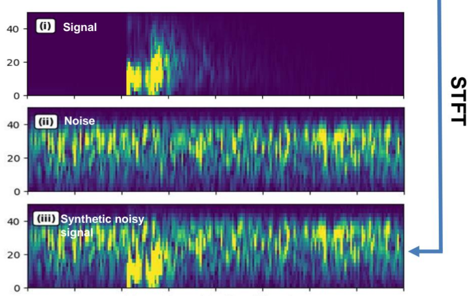

Figure 3: Input of Our Neural Network

Model & Results

Cross-entropy loss function

$L(p, y) = -[y\,log(p) + (1 - y)\,log(1 - p)]$

Convolutional Neural Network encoder-decoder Architecture

- U-Net
- DeepLab v3+ with Xception as backbone

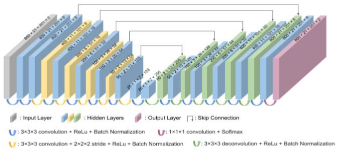

Figure 4: U-Net Based Network Architecture

U-Net based model performance

Model	Hyperparameters				Cross-entropy loss	
	Learning Rate	Batch Size	Dropout	Include Zero Signal	Training	Valid
Unet1	1.E-02	2	0.2	Yes	0.318	0.336
Unet2	1.E-04	2	0	No	0.342	0.441
Unet3	1.E-03	2	0	No	0.320	0.661
Unet4	1.E-02	2	0	No	0.321	0.723
Unet5	1.E-02	1	0.2	Yes	0.337	3.077
Unet6	1.E-02	1	0	No	0.340	174.427

- A higher learning rate tends to fasten convergence and results in a lower training error
- A batch size of two helps convergence
- Dropout decreases variance

Xception based model performance

Model	Hyperparameters				Cross-entropy loss
	Learning Rate	Batch Size	LR Decay Rate	Weight Decay	Training
Xception1	1.E-05	1	0.98	1.E-08	0.529
Xception2	1.E-03	1	0.99	0	0.644
Xception3	1.E-03	1	0.95	1.E-04	0.777
Xception4	1.E-02	1	0.98	1.E-08	0.785

- A lower leaning rate tends to help gradient descent to achieve lower training error
- Xception based model is hard to converge because of its extreme complexity

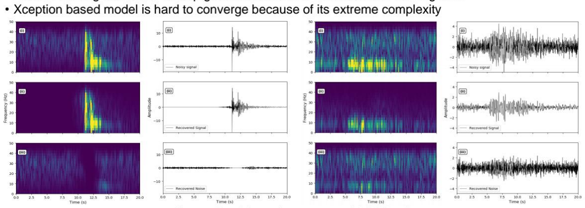

Figure 5. Denoising performance on real SAFOD seismograms

SAFOD Location

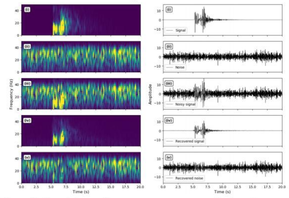

Figure 6. Denoising performance on unseen synthetic seismogram

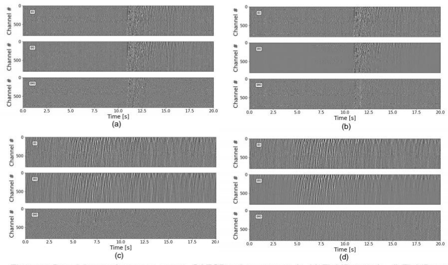

Figure 7: Denoising performance on two SAFOD seismograms, (a, b) FieldData1; (c, d) FieldData2: (a, c) Baseline model; (b, d) U-Net based model. Real noisy signal are plotted in panels (i). Panels (ii) shows the denoised signal. The recovered noise is shown in panels (iii).

Evaluation Matrix – Signal-to-Noise Ratio (SNR)

$SNR = 10\,log_{10}(\sigma_{signal} / \sigma_{noise})$

SNR performance with Baseline (wavelet filter) and Unet1

Data set	Noisy Signal SNR (dB)	Denoised Signal SNR (dB)	Baseline Model SNR (dB)
Validation Data Sample 1	3.78	18.18	3.72
Validation Data Sample 2	1.87	18.46	3.31
Validation Data Sample 3	0.84	14.46	2.50
Field Data Sample 1	0.77	3.69	2.21
Field Data Sample 2	6.52	13.00	5.50

Conclusion

U-Net is much easier to train and converge than Xception because of the simplicity of the model.

U-Net achieves better SNRs of the recovered signal than the baseline model by factors of:

- 5.416, for three validation data
- 2.016, for two field data.

Reference

[1] Zhu, Weiqiang, S. Mostafa Mousavi, and Gregory C. Beroza. "Seismic signal denoising and decomposition using deep neural networks." arXiv preprint arXiv:1811.02695 (2018).

[2] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." International Conference on Medical image computing and computer-assisted intervention. Springer, Cham, 2015.

[3] Chen, Liang-Chieh, et al. "Encoder-decoder with atrous separable convolution for semantic image segmentation." Proceedings of the European Conference on Computer Vision (ECCV). 2018