Deep and Convolutional Neural Networks for identifying vertically-propagating incoming seismic wave motion into a truncated, heterogeneous, damped soil column

Shashwat Maharjan & Chanseok Jeong, PhD

Solid, Waves, Intelligence, and Mechanics (SWIM) Lab
School of Engineering and Technology
Central Michigan University

June 2, 2022

Presentation Overview

- Identifying input seismic wave motion on soil bedrock based on measurements at the ground surface, under a known soil profile;
- Input features are measured motion at a sensor on top of a soil column and output features are predicted targeted seismic input motion;
- We discuss how training data for such problems may be generated;
- Investigate the effectiveness and computational cost of using ANNs for such problems.

Existing methods

Current practice for identifying the input seismic wave motion on the bedrock relies on a procedure known as deconvolution which works as follows:

- the measured waveform on the ground surface is transformed into the frequency domain;
- the transfer function of the one-dimensional soil profile is computed; and
- the measured waveform in the frequency domain is multiplied by the inverse of the transfer function, and this product is then transformed back into the time domain.

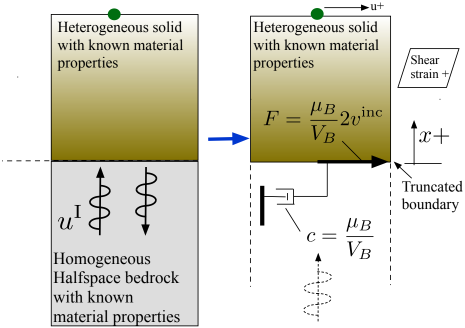
This procedure gives us the time-domain waveform of the incident wave on the bedrock.
Refer to [Mejia and Dawson, 2006, Ju, 2013, Poul and Zerva, 2018a, Poul and Zerva, 2018b].

Limitation of this method

- Applying the deconvolution to a two- and three-dimensional case is impossible!
- Full-waveform inversion of seismic inputs can be used for a two- and three-dimensional case, but it is computationally expensive (not applicable for real-time inversion).

We address all of the concerns of this method by implementing ANNs!

Problem definition



(A) a site of interest: we identify incoming vertically-propagating seismic wave signal at the soil-bedrock interface.

(B) a truncated, simplified model of the site of interest.

[Jeong and Seylabi, 2018] showed that the elastic bedrock can be substituted with a finite-size truncated system where a viscous damper is attached to the bottom of the soil layer.

Governing Equation

Wave motion within a semi-infinite, one-dimensional soil column is described by the following partial differential equations.

$$\frac{\partial}{\partial x}\left[\mu(x)\frac{\partial u(x,t)}{\partial x}\right] = \rho(x)\frac{\partial^2 u(x,t)}{\partial t^2}, \qquad 0 < x < L, \quad 0 < t < T, \tag{1a}$$

$$\mu(x)\frac{\partial u(x,t)}{\partial x} = \frac{\mu_B}{V_B}\left[\frac{\partial u(x,t)}{\partial t} - 2v^{\text{inc}}(t)\right], \qquad x = 0, \tag{1b}$$

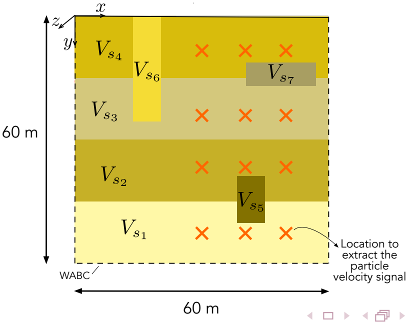
$$\mu(x)\frac{\partial u(x,t)}{\partial x} = 0, \qquad x = L, \tag{1c}$$

where,

- $v^{\text{inc}}(t)$ is the particle velocity of unknown incoming seismic wave;
- $\mu(x)$ and $\rho(x)$ are shear modulus and mass density;
- $u(x,t)$ represents the particle displacement in the medium;
- μ_B and V_B denote shear modulus and shear wave velocity of the bedrock.

Output-layer data generation

- For our waveform randomizer, we consider anti-plane shear waves propagating in a two-dimensional domain, which is appropriately truncated by using wave-absorbing boundary conditions;
- We take advantage of reflection and refraction in a heterogeneous domain, in order to generate complex waveforms;
- Reduce bias and increase randomness.



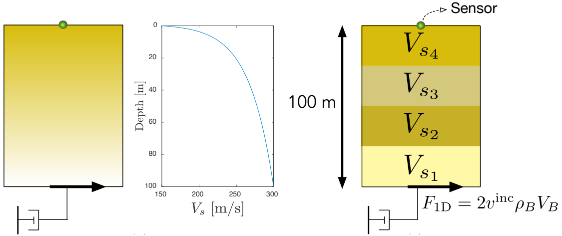
Input-layer data generation

- The waveforms generated in the previous subsection are now used as the incident wave signal (i.e., $v^{\text{inc}}(t)$) in a one-dimensional wave simulator;
- The one-dimensional wave system appropriately accounts for the truncation boundary by using a viscous damper, and uses a shear force proportional to the incoming incident wave to drive the system;
- A sensor is placed at the top surface of the soil column to record the displacement field of the wave response induced by each $v^{\text{inc}}(t)$.

Input-layer data generation

In this study, we consider two different soil profiles in the one-dimensional wave system:

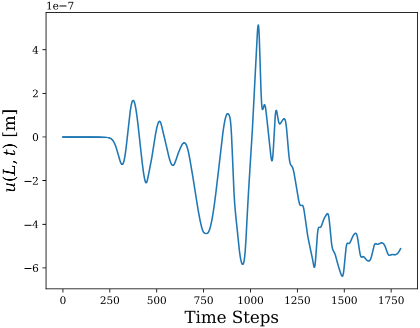
- A soil column with an asymptotically-varying shear wave speed;
- A 4-layer soil column.



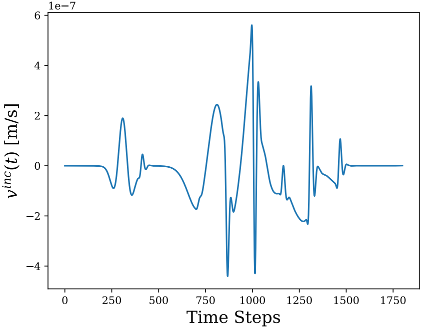
(a) Asymptotically-varying shear wave (b) 4-layer soil column

We model material damping using Rayleigh damping in discrete form.

Input and Output Waveforms

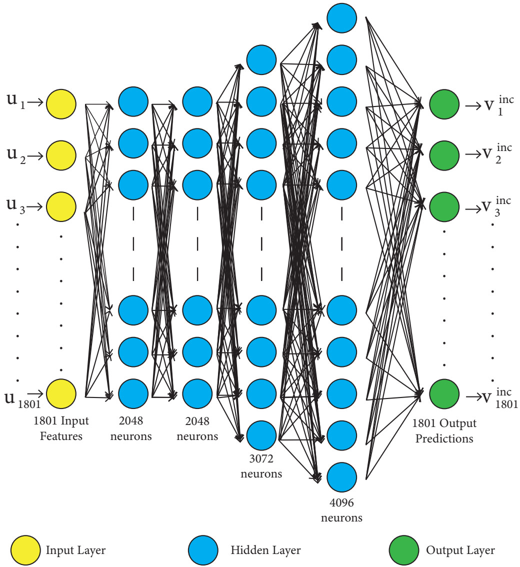


(a) Input-layer waveform

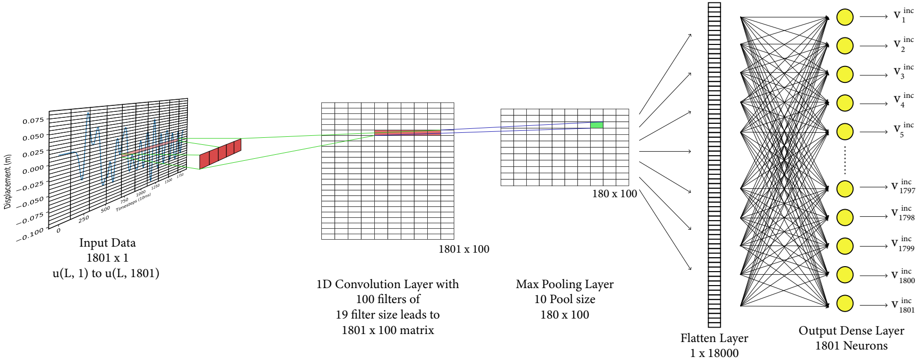


(b) Output-layer waveform

Deep Neural Network (DNNs)



Convolutional Neural Network (CNNs)



Used Error function

$$\epsilon_i = \sqrt{\frac{\sum_{j=1}^{m}\left(v_{ij}^{\text{inc}} - v_{ij}^{\text{inc}}\right)^2}{\sum_{j=1}^{m}\left(v_{ij}^{\text{inc}}\right)^2}} \times 100\,[\%]. \tag{2}$$

where,

- m is the number of time step feature of data;
- v_{ij}^{inc} is the i-th record and j-th time step feature of the targeted output-layer data; and
- v_{ij}^{inc} is the associated ANN-predicted output-layer data.

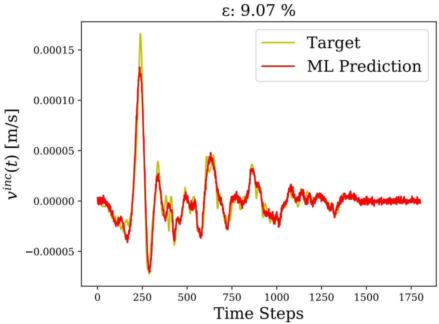
Performance ANNs on both soil column test datasets

Table listing the error statistics in percentage.

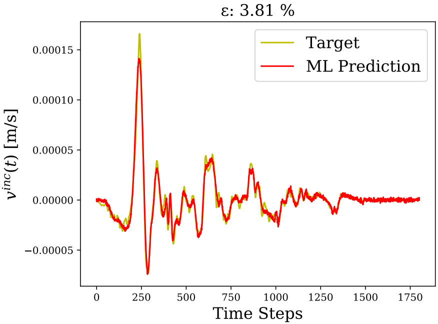
Data set	Example 1: Asymp.-varying soil DNN	CNN	Example 2: Multi-layer soil DNN	CNN
Mean error of the test data set	0.27%	0.05%	0.26%	0.06%
Median error of the test data set	0.21%	0.04%	0.19%	0.05%
Maximum error of the test data set	2.37%	0.83%	2.73%	0.80%
Minimum error of the test data set	0.07%	0.02%	0.08%	0.02%
Error for the Northridge Earthquake signal	9.07%	3.81%	7.68%	3.22%

- Our trained DNN and CNN are also examined for the reconstruction of a real-world incident waveform.
- We use 1994 Northridge earthquake ground motion signal (blind test data), which is considerably different from records we generated with our waveform randomizer.

Performance on Northridge data - Asymp-varying soil



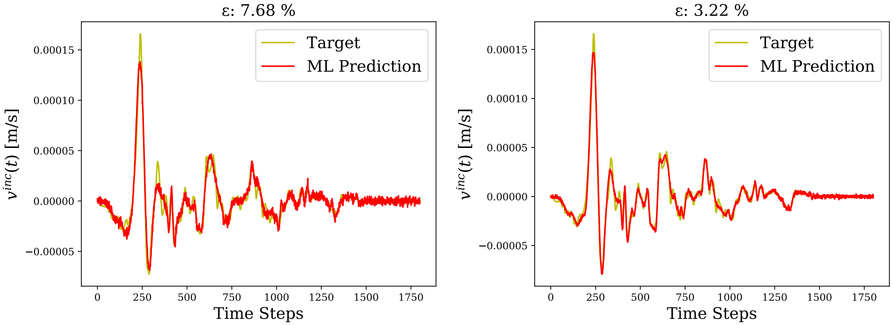
(a) DNN



(b) CNN

The reconstruction of the 1994 Northridge earthquake incident waveform, using the DNN and CNN, for the soil column with an asymptotically-varying shear wave speed.

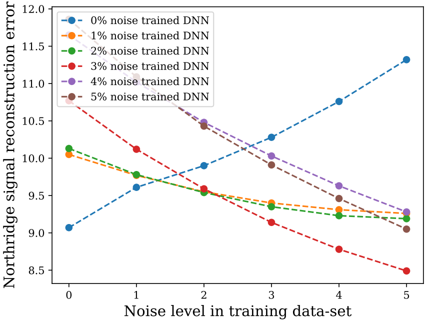
Performance on Northridge data - Multi-layer soil



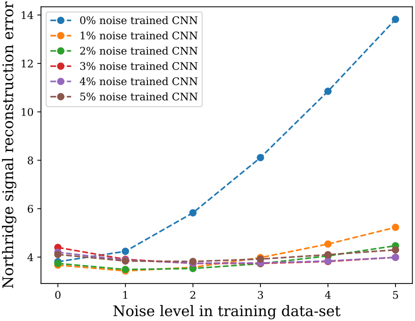
(a) DNN (b) CNN

The reconstruction of the 1994 Northridge earthquake incident waveform, using the DNN and CNN, for the multi-layer soil column.

Effect of noise on performance of ANNs



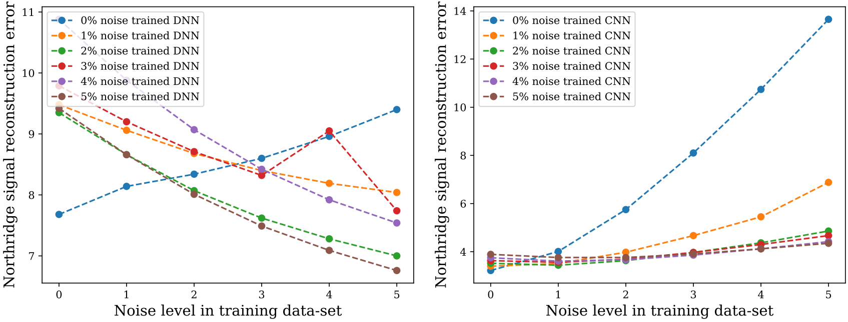
(a) DNN



(b) CNN

Prediction error of the Northridge waveform, using DNN and CNN, and various noise levels, for the soil column with an asymptotically-varying wave speed soil column.

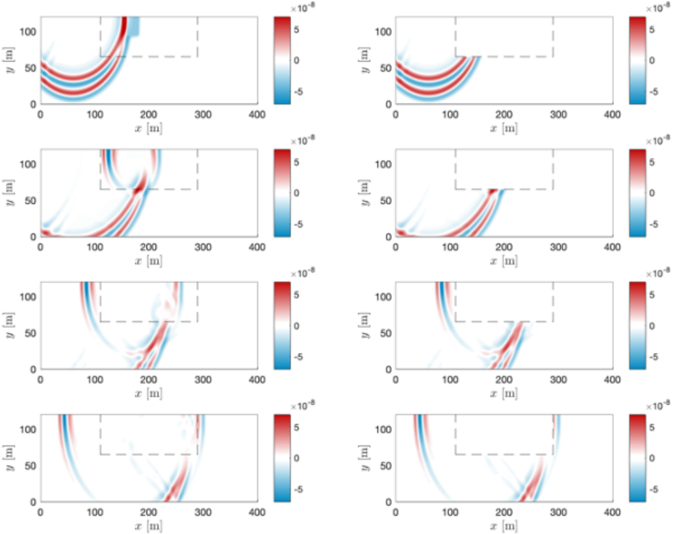
Effect of noise on performance of ANNs



(a) DNN (b) CNN

Prediction error of the Northridge waveform, using DNN and CNN, and various noise levels, for the multi-layer soil column. Include Figure 26 and 27 from the paper in the presentation.

Real-time computing seismic metaforce for active seismic control.



Conclusion

- We demonstrated the effectiveness of using a data-informed framework for identifying the incoming seismic wave motion;
- Showed the ability of both DNN and CNN to learn important feature relationships between the input- and output-layer data sets;
- We also studied the effect on the performance of designed ANNs when we tested them on a realistic seismic signal;
- We plan to extend this data-informed method to a multi-dimensional setting;
- This would allow the reconstruction of incoming seismic motions in a 3D domain in real-time.

Acknowledgement

- National Science Foundation, under Award CMMI-2044887 and CMMI-2053694
- Faculty Research and Creative Endeavors (FRCE) Research Grant-48058 at Central Michigan University
- Office of Research and Graduate Studies (ORGS) at Central Michigan University

Related Publication

- (202x) Deep and Convolutional Neural Networks for identifying vertically-propagating incoming seismic wave motion into a truncated, heterogeneous, damped soil column (under review).
- (202x) Seismic Meta Force for Vibration Isolation of Structures (in preparation).

THANK YOU!