Geotechnical Site Characterization via Deep Neural Networks: Recovering the Shear Wave Velocity Profile of Layered Soils

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Abstract

The mechanical property of soils is a vital part of seismic hazard analysis of a site. Such properties are obtained by either in-situ (destructive) experiments such as crosshole or downhole tests, or by non-destructive tests using surface wave inversion methods. While the latter is more favorable due to the cost-efficiency, there are challenges mostly due to computational need, non-uniqueness of inversion results, and fine-tuning parameters. In this article, we use a deep learning framework to circumvent the above-mentioned limitations to output soil mechanical properties, requiring dispersion data as input. Our trained model performs with high accuracy on the test dataset and shows satisfactory performance compared to the ensemble Kalman inversion technique. We finally propose a framework to extend the method to higher dimensions by numerically solving the wave equation in a two-dimensional medium.

1 Introduction

One-dimensional (1D) site response is the most prevalent method to assess the seismic hazard. In this approach, the 1D wave equation is solved in a layered soil medium under certain initial and boundary conditions. Numerical methods such as Finite Difference (FD) and Finite Element (FE) are among the commonly used methods to simulate the medium subjected to a time-series at the bottom of a discretized domain to represent earthquake loading. Given the dynamic nature of the problem, for each soil layer, three separate parameters are needed ($3n$ parameters for an n-layered soil). However, these parameters are not easily available, and obtaining them requires huge machinery for in-place testing. Therefore, researchers and engineers resort to inversion techniques, such as

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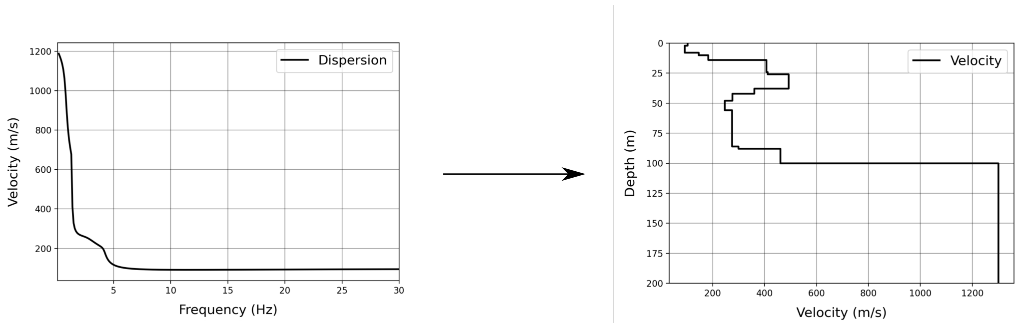

Figure 1: An example of dispersion curve (phase velocity versus frequency) with corresponding soil shear wave velocity profile (variation of velocity with depth). The trained model gets the data on the left and returns the data on the right.

ensemble Kalman inversion [1], stochastic direct search algorithm [2], uniform Monte Carlo method [3], and fully Bayesian Markov chain Monte Carlo method [4] to name but a few, to reconcile the issues. Such techniques mostly rely on ground surface acceleration time-series and dispersion data to infer the mechanical properties of soil layers. A comprehensive review of inversion techniques for this application can be found in [1].

In general, dispersion data is more accessible than time-series, the reason that the majority of studies rely on them for inversion purposes [5, 1]. However, due to the non-uniqueness of solutions, researchers have tried to better constrain the uncertain parameters by including time-series data in the inversion process [1]. In this article, we use only dispersion data to invert for the mechanical properties of a soil medium using a Deep Neural Network (DNN) model. The data set includes a large number of soil profiles and their corresponding dispersion curves. Our approach uses these theoretical dispersion curves of various soil columns to train a model that is able to return the soil shear wave velocity profile with high accuracy. In the next section, we detail the methodology. This includes the problem statement, the generation of training data, the architecture of the network, and hyperparameter tuning. Next, we assess the capability of the network on a test dataset. Finally, we compare the network's performance versus the state-of-the-art ensemble Kalman inversion technique [6].

2 Methodology

2.1 Problem Statement

The problem includes finding u given y_i as input. Eq 1 frames this as an inversion problem.

$$y_i = G_i(u) + \eta_i \tag{1}$$

where $u \in \mathbb{R}^k$ shows k unknown parameters in the inversion process, $y_i \in \mathbb{R}^m$ shows m observation points, $\eta_i \in \mathbb{R}^m$ is zero-mean Gaussian noise added to the observation data for training process, and G_i is a forward nonlinear function. The Deep Neural Network tries to learn the inverse of G function ($H : u = H_i(y_i - \eta_i)$). In the above equation, y_i is the dispersion data which shows the phase velocity values of the surface wave as a function of frequency, and u demonstrates the shear wave velocity value of soil profile. Figure 1 shows an example of a dispersion curve and soil shear wave velocity profile.

2.2 Dataset

For training data, we inquire shear wave velocity profiles of California from the PySeismosoil package [7]. PySeismosoil package returns an average shear wave velocity profile given Vs_{30} (shear wave velocity of the top $30\,m$ of soil) and Z_1 (depth of rock) values. Table 1 shows the ranges of values that are used to generate the profiles from PySeismosoil. The generated profiles are later randomized to expand the dataset with new examples.

Table 1: Range of parameters for training set generation.

Network	
Layer	Description
Vs_{30} (Shear wave velocity of top $30\,m$)	$200 - 800\,(m/s)$
Z_1 (Depth at which shear wave velocity becomes $1000\,m/s$)	$1000 - 4000\,(m)$

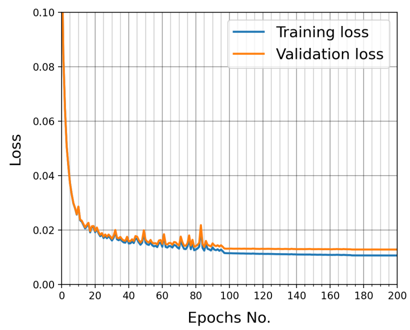

Figure 2: Variation of training and validation losses as a function of epochs.

Table 2: Architecture of network.

Network		
Layer	Description	Size
Input	Regular	$\mathbb{R}^{299}$
HL 1	Regular	$\mathbb{R}^{299}$
HL 2	Resnet	$\mathbb{R}^{299}$
HL 3	Resnet	$\mathbb{R}^{299}$
HL 4	Resnet	$\mathbb{R}^{299}$
HL 5	Regular	$\mathbb{R}^{299}$
Output	Regular	$\mathbb{R}^{250}$

The theoretical dispersion curves are calculated using GEOPSY [8] which includes the fundamental mode of Rayleigh wave. The data set consists of $y_i \in \mathbb{R}^{299}$ (dispersion data), which covers frequencies in the range of $f \in [0.1, 30]\,Hz$. Besides, $u \in \mathbb{R}^{250}$ which is a vector with soil shear wave velocity at every $2\,m$ in depth (total soil column thickness of $500\,m$). The data set is finally divided into $80/10/10$ partitions for training, validation, and testing.

2.3 Deep Neural Network

We use a deep neural network in this study with 5 hidden layers to perform regression analysis and each hidden layer consists of ResNet units [9]. A ReLU activation function is added to hidden layers. Adam optimizer [10], L_2 norm cost function, and learning rate of $lr = 10^{-4}$ are used for the learning purpose. Early termination is also performed to prevent overfitting. Table 2 shows the architecture of the deep neural network.

Moreover, Figure 2 shows the loss variation for training and validation set as a function of epochs. We started with 200 epochs but terminated the learning after 100 iterations for the results that will be shown in this article.

3 Results

3.1 Test dataset

As was previously mentioned, 10% of data was reserved for testing purposes. Figure 3 shows the performance of the trained model on the test data set. Each point on this figure illustrates one component of the output vector (remember that $u \in \mathbb{R}^{250}$) versus the corresponding true value. In a perfect model, all the points should lie on the $y = x$ line (shown by a dashed line in the figure). While the model is not perfect as expected, the performance is satisfactory in terms of accuracy as shown by the r^2 value between predicted and target values.

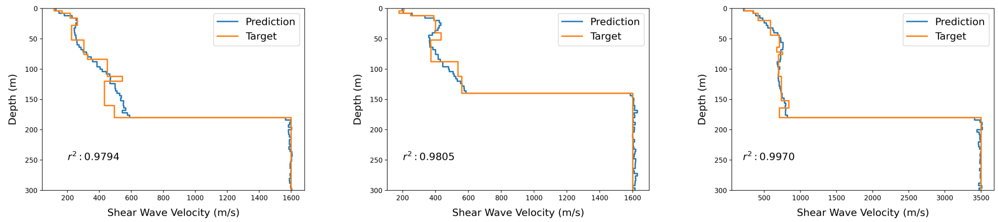

Figure 4: Three randomly chosen examples from test dataset. Each figure shows the true output "Target" and the prediction of DNN.

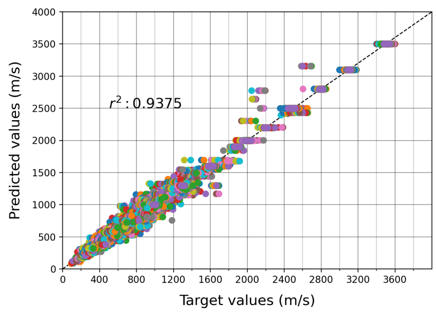

Figure 3: Comparison of predicted versus true values for test dataset. Each point on the figure shows one component of output array.

Furthermore, Figure 4 shows three randomly chosen data points from the test data set. For each example, the dispersion data (input of NN) and corresponding shear wave velocity profile (Target) are obtained. The input is fed into the model and the prediction of the model versus true values is depicted in this figure. As can be seen, the model can predict the Target values with high accuracy. Note the sudden jumps in the "target" that are not fully captured by the model. This can be partially attributed to the model trying to avoid overfitting. We also tested Stochastic Gradient Descent (SGD) for training which seemed to be able to better capture the sudden jumps. However, it would take significantly longer iterations to reach a satisfactory loss level.

3.2 Comparison with ensemble Kalman inversion method

Seylabi et al. (2020) showed an application of ensemble Kalman inversion (EKI) to invert for soil shear wave velocity profile given dispersion data as input [1]. Figure 5 shows a comparison of predictions using the model trained in this study versus the results of EKI reported by [1]. As can be seen, the network is able to predict target values with satisfactory precision and performs well in comparison to the EKI method. The main advantage of the DNN model used here over the EKI is its ability to predict accurate results needless of any sort of initialization and parameter tuning. This is important from a practical standpoint. A user can easily perform the inversion without an in-depth knowledge of the network's architecture of the training process.

4 Conclusion

In this study, we train a DNN model that takes dispersion data as input and returns the shear wave velocity profile of a soil medium as output. The training dataset is generated using 1D shear wave velocity profiles of California [7] and dispersion data is calculated using GEOPSY [8]. The model was evaluated on a test dataset in addition to the recently published work of Seylabi et al. (2020) [1] where they used the ensemble Kalman inversion method. In both cases, the performance was shown to be satisfactory, while the model doesn't need any further fine-tuning or initialization as required by EKI. For a future part of this study, we intend to extend the current approach to $2D$ problems where

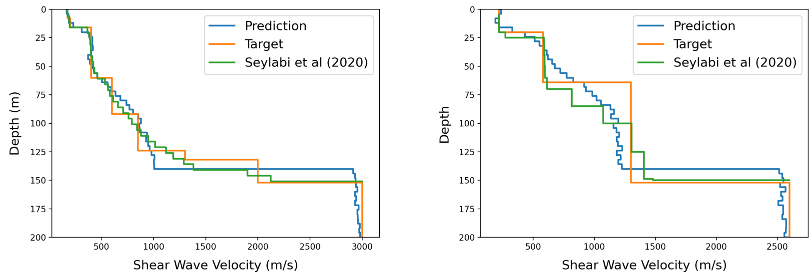

Figure 5: Comparison of current model versus the published results of Seylabi et al (2020) [1]

training data will be generated by solving the wave equation using the Finite Element method. This problem is known to be difficult to tackle even with modern statistical techniques, and few studies approached it such as [11].

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