4th International Conference on
Earthquake Geotechnical Engineering
June 25-28, 2007
Paper No. 1133

AN INVERSE ANALYSIS APPROACH TO EXTRACT DYNAMIC NONLINEAR SOIL BEHAVIOR FROM DOWNHOLE ARRAY DATA

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ABSTRACT

Non-linear dynamic soil behavior is commonly obtained from laboratory tests. The loading paths from lab tests, however, are significantly different from those soil experiences in the field and are not necessarily representative of anticipated soil behavior during earthquake shaking. Recently, increasing number of downhole arrays are deployed to measure motions at the ground surface and within the soil profile, which can enhance our understanding of local site effects. Moreover, these measurements also provide opportunities to gain insights into the situ dynamic soil behavior. A novel inverse analysis framework, SelfSim (Self learning simulations), uses downhole array measurements to extract the underlying soil behavior is introduced. This framework integrates site response analysis and field measurement and, in addition to extracting underlying dynamic soil behavior, develops a neural network based constitutive model representing in-situ soil behavior. The soil model can continuously evolve using additional field information. The resulting soil model, used in a site response analysis, can provide correct ground response. The performance of the algorithm is demonstrated using synthetic and measured downhole array data from Lotung array in Taiwan.

Keywords: inverse analysis, dynamic soil behavior, downhole array, site response analysis

INTRODUCTION

Observations from earthquakes over the past 40 years have shown the importance of local site conditions on propagated ground motion. Strong motion records from many earthquakes including 1957 San Francisco Earthquake, 1989 Loma Prieta, and 1999 Chi-Chi events show significant differences between soil sites and nearby rock sites responses. The 1985 Mexico City earthquake has shown that soft soils can cause significant amplification and resonance of the ground motion resulting in significant damage even at large distances from the earthquake source.

Conventional site response analysis models are used to predict seismic site response at a site including acceleration, velocity, and displacement at ground surface and within the soil column. The accuracy of predictions depends on the representation of cyclic soil behavior. Laboratory tests are often used to measure or evaluate dynamic soil behavior. Then, the measured soil behavior is used to develop soil models which are implemented in a site response analysis model. However, the loading paths from lab tests are significantly different from those soil experiences in the field (Kramer, 1996) and are not necessarily representative of anticipated soil behavior.

Recently, increasing number of downhole arrays are deployed to measure motions at the ground surface and within the soil profile. These arrays provide the real data necessary to better understand local site effects and in situ dynamic soil behavior. They also provide a check on the accuracy of site

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response analysis models. Ad-hoc approaches are sometimes adopted to adjust soil model properties to match field observations. The approaches are not always successful and do not necessarily provide additional insights into the seismic site response and underlying dynamic soil behavior. On the other hand, Zeghal et al. (1995) used a linear interpolation approach (nonparametric identification) to estimate shear stress and strain seismic histories from these arrays. Soil behavior, however, identified by this method only represents averaged behavior between two measurement points. Recently, other system identification approaches (parametric identification) including time domain approach (Glaser and Baise, 2000) and frequency domain approach, (Elgamal et al., 2001; Harichance et al., 2005) provide better estimates of soil dynamic properties (shear stiffness and damping ratio) via vertical array measurements. Frequency domain methods can only identify the equivalent stiffness and damping of the system under a given level of shaking. Time domain methods identify the change of stiffness and damping ratio at each time interval, however these time-varied parameters still cannot be readily integrated into a material constitutive model for future use in site response analysis. Current approaches do not fully benefit from field observations. There is a need to better integrate field observation with numerical simulations of seismic site response. This paper describes development and application of novel inverse analysis techniques to gain greater insights into seismic site response and dynamic soil behavior from downhole arrays.

EXTENSION OF SELFSIM, SELF-LEARNING SIMULATIONS, TO 1-D SEISMIC SITE RESPONSE

SelfSim, self learning simulations, is an inverse analysis framework that implements and extends the autoprogressive algorithm (Ghaboussi et al., 1998). The algorithm requires two complimentary sets of measured boundary forces and displacements used as input boundary conditions in two complimentary numerical analyses of the boundary value problem. The analyses produce complimentary pairs of stresses and strains that are used to develop a Neural Network (NN)-based material constitutive model. The resulting material model can then be used in the analysis of new boundary value problems. SelfSim has been used to extract material behavior from non-uniform material tests (Sidarta and Ghaboussi, 1998, Shin and N., 2000, Pande and Shin, 2002). Hashash et al. (2003) demonstrated the feasibility of extracting material constitutive behavior from measurements of lateral wall deflections and surface settlements due to construction of a braced excavation. So far all applications of SelfSim inverse analysis approach have been applied to static problems. Hashash and Park (2002) proposed conceptually the possible extension of SelfSim concept to seismic data from downhole arrays. However, unlike static problems, applying SelfSim in 1D seismic site response requires new developments. The details of these developments are described in the following section.

SelfSim framework application to seismic site response problems is illustrated in Figure 1. In a downhole array, step 1, the ground response corresponding to this base shaking is measured at selected depths within the soil profile. The input base shaking and the corresponding measurements within the soil profile represent complementary sets of field observations. The measured data is used in two parallel site response analyses and a NN material model is used to represent cyclic soil behavior in lieu of using a conventional material model. As the soil behavior is unknown, the NN material model is initialized to reproduced linear visco-elastic response over a limited strain range.

In Step 2a of SelfSim a conventional site response analysis using the current NN soil model is performed. The measured acceleration from the deepest point in a vertical array is applied at the bottom of the soil column as a conventional time-domain non-linear site response analysis. In this analysis the stresses and strains are computed throughout the soil column based on dynamic equilibrium considerations. However, the computed displacements may not necessarily match recorded displacements within the downhole array. SelfSim stipulates that in this analysis since the applied boundary forces (due to base acceleration) are accurate then the corresponding computed equilibrium stresses provide an acceptable approximation of the true stress field experienced by the soil.

In Step 2b of SelfSim a parallel site response analysis using the same NN soil model is performed. In addition to base shaking, displacements integrated from recorded acceleration time series within the downhole array are imposed in the nonlinear site response analysis. In this analysis stresses and strains are also computed throughout the soil column. SelfSim stipulates that since the applied displacements are accurate then the corresponding computed equilibrium strains provide an acceptable approximation of the true strain field experienced by the soil.

The stresses from Step 2a and the strains from Step 2b form stress–strain pairs that approximate the soil constitutive response. These pairs are used to retrain and update the NN material model. The entire process is repeated several times using the entire time series until analyses of Step 2a provide ground response similar to that measured in the array. At this point, SelfSim has extracted sufficient information about the dynamic soil response to reproduce field measurements. The resulting NN constitutive model can be used in the site response analysis of other events, Step 3, whereby the soil experiences strains similar to those experienced during the learning process.

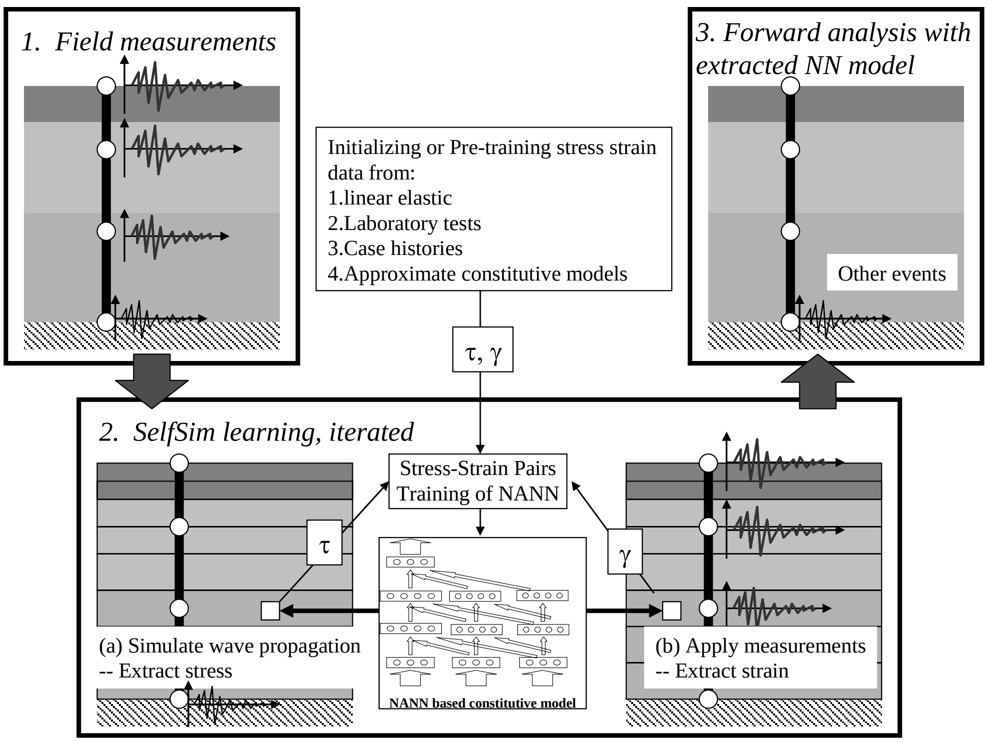

Figure 1. SelfSim algorithm applied in downhole array

NUMERICAL IMPLEMENTATION OF SELFSIM FOR 1-D SEISMIC SITE RESPONSE

In order to implement SelfSim algorithm for seismic site response the following is needed:
1. A site response analysis procedure for Step2a,
2. A site response analysis procedure for Step2b,
3. A NN material model architecture that is capable of representing cyclic soil behavior.

Site response analysis procedure for Step 2a

In Step2a, the measured acceleration from the deepest point in a vertical array is applied at the bottom of the soil column as a conventional site response analysis, Figure 2a. The base acceleration is converted to equivalent forces imposed on lumped masses, which represent the soil column.. A modified version of the 1-D time-domain non-linear DEEPSOIL code (Hashash and Park, 2001), www.uiuc.edu/~deepsoil, capable of utilizing a NN material model is used.

Site response analysis procedure for Step 2b

In Step2b displacements integrated from recorded acceleration time series at different depths are imposed in a 1-D time domain nonlinear site response analysis. Equivalent forces due to base shaking are still imposed on soil column but more information (or constraints) is added by displacement measurements, Figure 2b. DEEPSOIL is modified to handle this type of analysis.

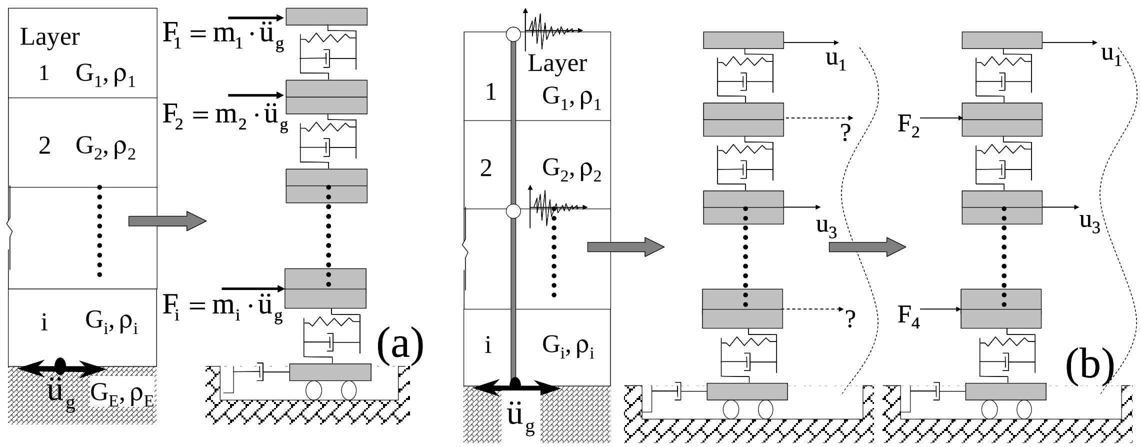

Figure 2. Site response analysis procedures used in SelfSim; a) conventional site response analysis model: acceleration is input at bedrock and converted as equivalent force applied to lumped masses; (b) site response analysis with composite force and displacement (measurements from array) boundary conditions.

NANN to represent cyclic soil constitutive behavior

The early work of Ghaboussi and his co-workers (Ghaboussi et al., 1991; Ghaboussi and Sidarta, 1997) shows that a Neural Network, NN, can be used to define material constitutive relation through 'training' using stress-strain data. If the data contains adequate relevant information, the trained neural network can generalize material behavior to new loading cases. Many researchers (Ellis et al., 1995; Zhu et al., 1998; Penumadu and Zhao, 1999) have shown that neural networks are capable of representing soil nonlinear behavior for static problems, whereby only monotonic loadings are applied.

The most common method for training a network is to map the X vectors onto Y vectors whereby a one to one relationship exists. Direct mapping method is not adequate to capture material behavior during cyclic loading- reloading. Basheer (2000) classifies mapping techniques into four categories: Function labelling, Function fragmentation, Quasi-sequential dynamic mapping, and Hybrid model. Quasi-sequential dynamic mapping is the most common technique to map cyclic behavior. It uses prior or history states of function (or data) to predict future states. Wu and Ghaboussi (1993) first used a 3-point history scheme to map concrete behavior in uniaxial cyclic compression to capture nonlinear and path dependent soil behaviour. In this paper a 3-point history scheme is used for the input layer of the NN material model consisting of current and prior states of stress and strain. The output layer consists of the updated state of stress. Two hidden layers are used as well.

APPLICATION OF SELFSIM TO SYNTHETICALLY GENERATED DOWNHOLE ARRAY DATA

SelfSim ability to extract underlying soil behaviour from downhole array measurements is first demonstrated using synthetically generated downhole array data. The advantage of using synthetically generated array data is that soil properties are known in advance and can be used to directly evaluate the extracted soil behavior.

Generation of synthetic downhole array data

The simulated soil profile is shown in Figure 3a. A broadband motion recorded during the Loma Prieta Earthquake is used to generate the synthetic recordings. DEEPSOIL is used to perform the site response analysis and develop the synthetic measurements using the built-in hyperbolic soil model. The measurements are taken at the rigid bedrock and at the surface as shown in Figure 3a. Although soil properties are uniform at the site, soil in various layers experiences different loading paths.

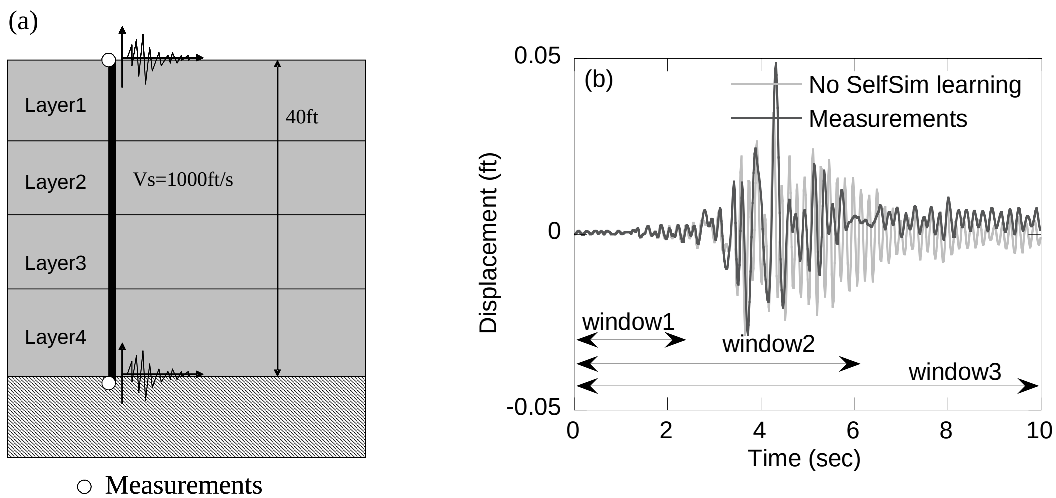

Figure 3. (a) Configuration of artificial downhole array, (b) Comparison of predictions prior to SelfSim learning with measurements at ground surface.

SelfSim learning of global response

Prior to SelfSim learning, the NN material model represents linear elastic behaviour within limited strain range. The same material model is used for all four layers. The computed surface motion using the initialized model is different from the measurements (target response) as shown in Figure 3b.

SelfSim learning is performed sequentially over three windows as shown in Figure 3b. Once SelfSim learning results in a model that can predict the measurement for a given window, learning is continued over the next window:

1. SelfSim Learning, window 1: After one SelfSim learning pass (Figure 4a), calculated surface displacements are very similar to the target measurements within this window. One pass is sufficient to learn the behavior within this window because the shaking is not strong and the soil column response is nearly linear elastic. The learned behaviour is not sufficient to correctly predict the behaviour over the entire recorded ground motion as illustrated in Figure 4a and Figure 4d (showing the response spectra).

2. SelfSim Learning, window 2: Two additional SelfSim learning passes are then performed using the window 2 data The computed response (pass 3) matches measurements very well (Figure 4b) over the learning window and can predict well the response at later shaking stages as illustrated in Figure 4b and Figure 4d. SelfSim learning of the first 6 sec extracts relevant information about cyclic soil behavior over the entire strain range experienced by the soil.

3. SelfSim Learning, window 3: Two additional SelfSim learning passes are then performed using the window 3 data (the entire period of shaking). Figure 4c and Figure 4d show a very good match with measurements. It appears that SelfSim is able to extract sufficient information about the soil behavior to accurately reproduce the field measurements.

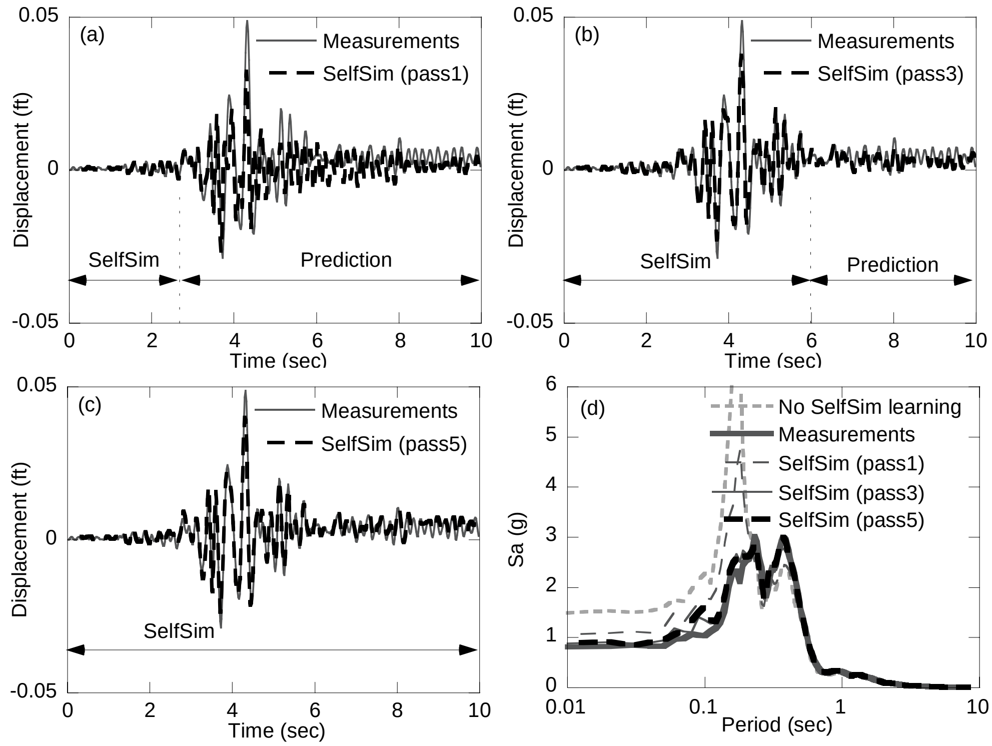

Figure 4. Comparison of surface displacements during SelfSim leaning (a) pass1 (b) pass3, (c) pass5 and (d) calculated surface response spectra.

Assessment of extracted nonlinear cyclic soil behavior

The extracted stress-strain behavior is compared to the target soil response in Figure 5. Although the extracted NN model does not exactly match the target response, it has evolved sufficiently to represent nonlinear and hysteretic behaviour of the soil. There is a good match with target response in small to middle strain ranges. The discrepancy at larger strains is due to insufficient information at these strain levels.

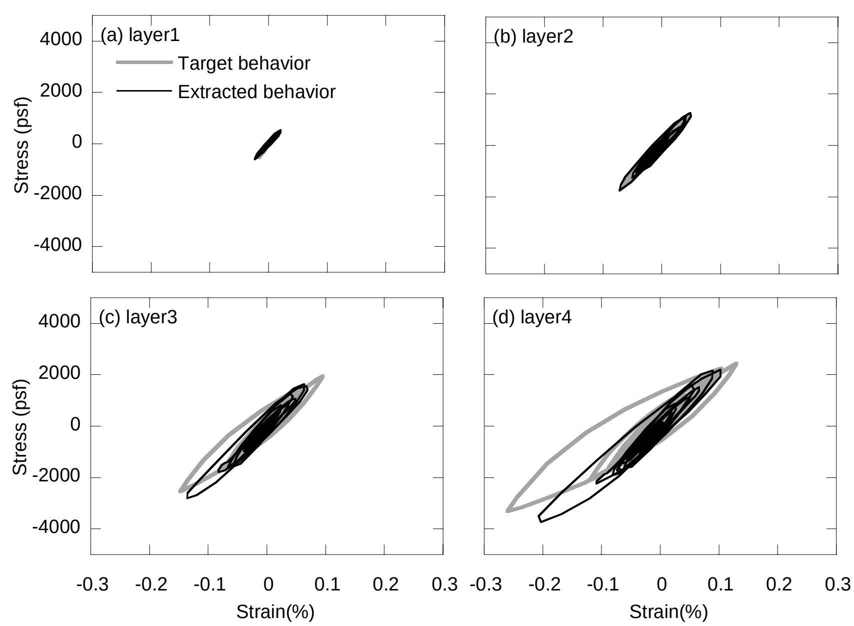

Figure 5. Comparison of extracted and target stress-strain response for all four layers

It is possible to reconstruct the backbone curve using extracted stress-strain data as shown in Figure 6a. The stress-strain data is re-assembled/reset between any two reverse points to generate as many monotonic curves. The data is used to curve fit a hyperbolic curve which then used to develop a modulus reduction curve as shown in Figure 6b. A damping curve is generated based on the identified backbone curve and Masing rule (Ishihara, 1996). The extracted behavior matches the target behavior very well except at large strains.

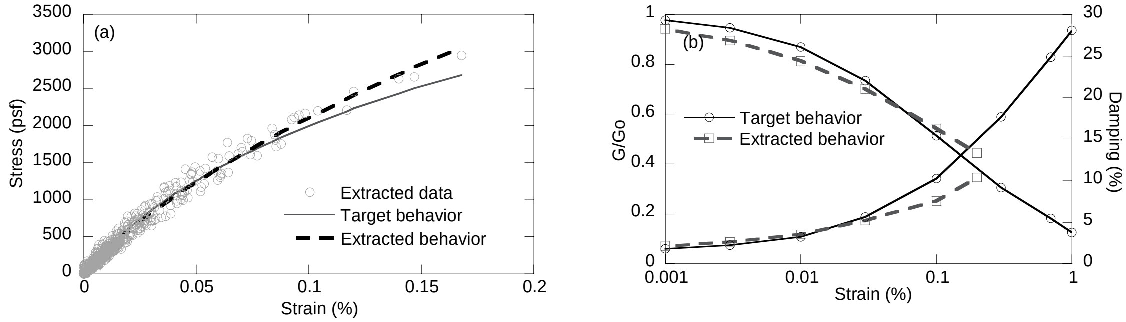

Figure 6. (a) Transform cyclic strain-stress curve to a set of monotonic curves, (b) construct modulus reduction curve and damping curve based on the best fit curve

APPLICATION OF SELFSIM TO MEASURED DOWNHOLE ARRAY DATA, LOTONG TAIWAN

The US Electric Power Research Institute (EPRI) in cooperation with the Taiwan Power Company (TPC) conducted a Large-Scale Seismic Test (LSST) at a site near Lotung, within the southwestern quadrant of the SMART1 array. Ground instrumentation included two downhole arrays (DHA and DHB). Only measurements of DHB vertical array are utilized since it is far from large scale structure model, and more closely reflects free-field site response. Figure 7a shows the configuration of vertical array, in which measurements are available at ground surface, 7m, 11m, 17m and 47m below the surface. Event no.7, with M= 6.8 and PGA=0.2g, is used in the paper. Only NS component of measurements is used in SelfSim learning.

SelfSim learning of global response

Four individual NN material models are assigned to soil layers between measurement points during SelfSim learning as shown in Figure 7b. Since the within motion is available, soil layers below the lowest sensor (47m) should be modelled as rigid base in time domain analysis (Kwok et al., 2006). The NN material models are initialized to represent small strain nonlinear behavior obtained from the lab tests (Anderson and Tang, 1989). Prior to SelfSim learning, the computed response at surface, 6m, 11m and 17m below surface given the NS motion at 47m using the initialized models is different form the measurements (target) as shown in Figure 8 and Figure 9. SelfSim learning is performed gradually as illustrated in Figure 7b. The best learning results are obtained by adding sensor information from bottom to top of the array mimicking the wave propagation. After several passes all measurements are then imposed simultaneously.

Figure 8 and Figure 9 show evaluation of SelfSim learning after 8 passes. SelfSim extracted sufficient information about the soil behavior to capture the measurements well. Some of the discrepancies might be attributable to incoherency of ground motions at different depth, which is not represented in a 1-D site response model (Finn et al., 1993). The extracted soil behavior and NN material models from the NS motion component are then used to predict the response for the EW component of the same event as shown in Figure 10. The measured behaviour is well predicted indicating that (1) SelfSim process successfully learns in-situ soil behavior at the site, and (2) the extracted soil behaviour is independent of the ground motion direction.

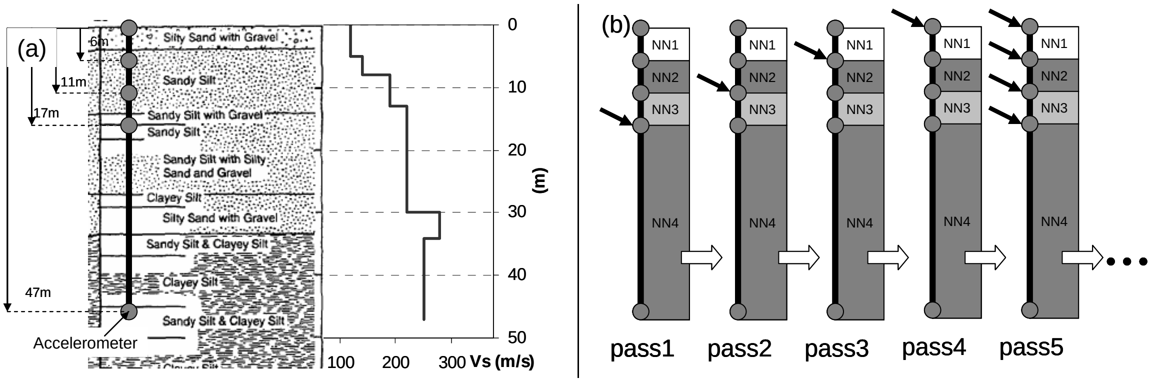

Figure 7. (a) Soil profile of LLST site and configuration of Lotung array. (b) SelfSim learning procedure applied in Lotung array.

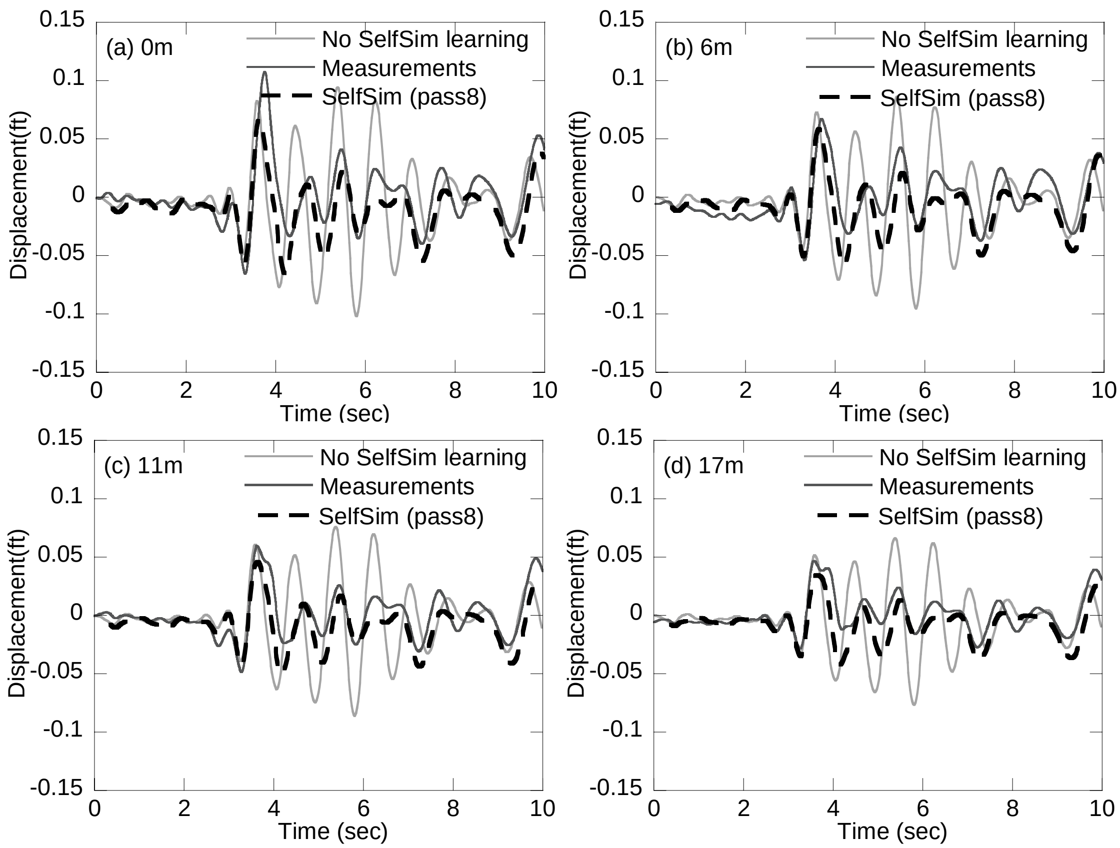

Figure 8. Comparison of computed displacements prior to and after SelfSim learning

Assessment of extracted behaviour

The extracted stress-strain behavior is shown in Figure 11a. The cyclic stress strain behavior is then used to interpret the backbone curve, Figure 11b. Figure 11c,d compare the extracted modulus reduction and damping curves to those from from lab tests (Anderson and Tang, 1989) and those from system identification inverse analyses (Elgamal et al., 2001). The extracted reduction curves are in the range of those from lab test and system identification method. The extracted damping is closer to that obtained from system identification.

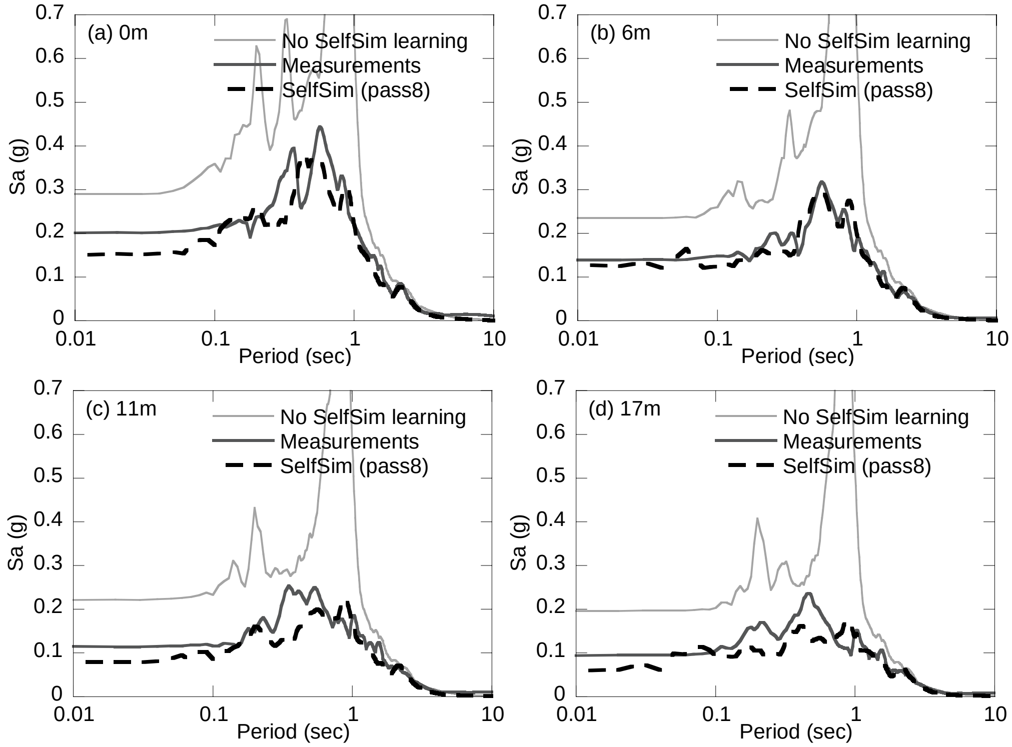

Figure 9. Comparison of acceleration response spectral prior to and after SelfSim learning with measurements

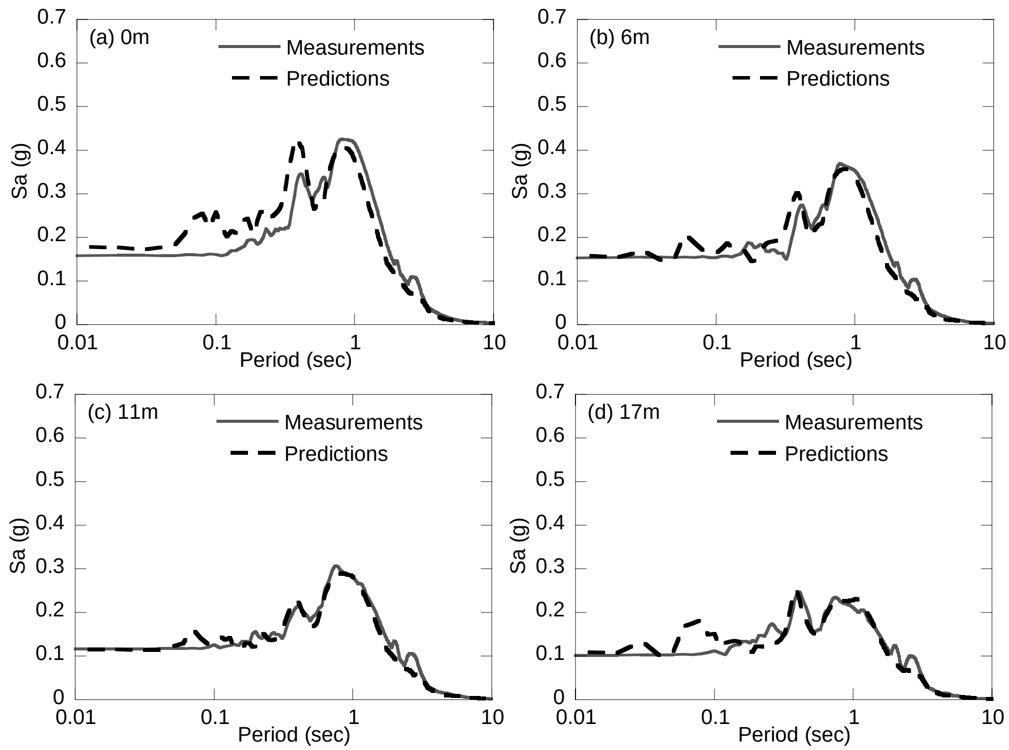

Figure 10. Comparison of predicted responses of EW components using extracted cyclic soil behavior based on the NS measurements.

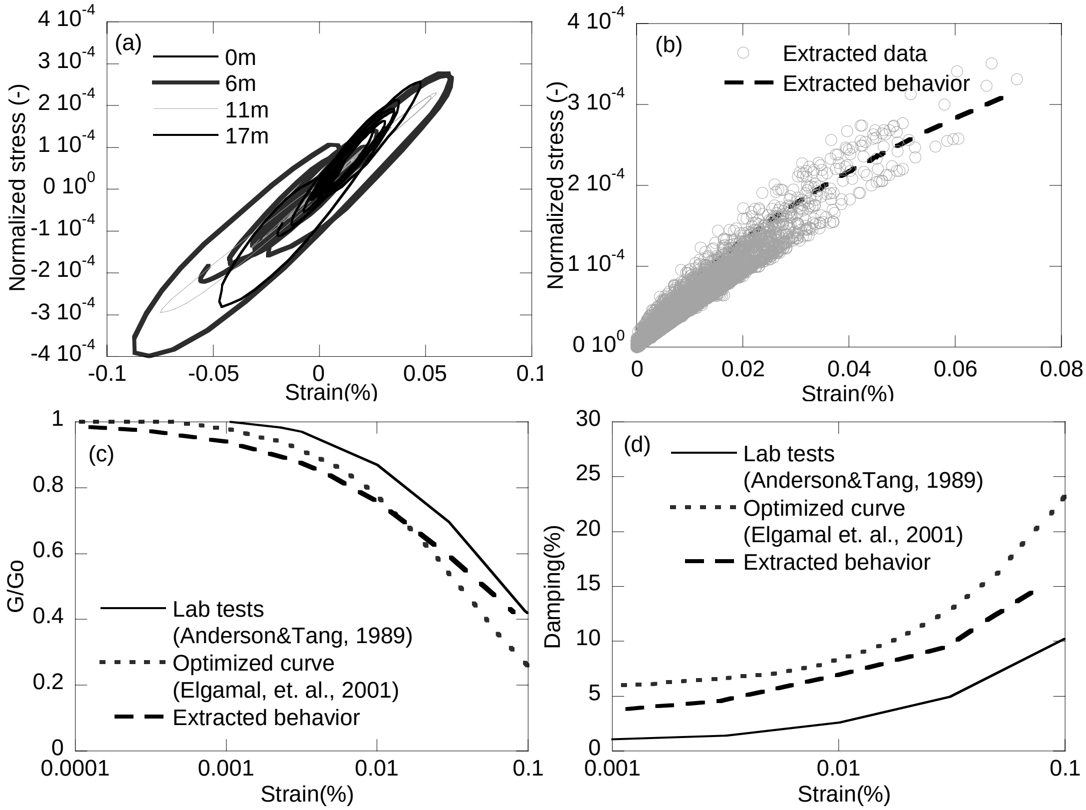

Figure 11. (a) Extracted strain-stress loop, (b) interpreted backbone curve, (c) comparison of modulus reduction curves (d) comparison of damping curves

SUMMARY AND CONCLUSION

A novel inverse analysis technique, SelfSim, is presented in this paper that provides a systematic approach for integrating downhole array measurements into numerical modelling of site response. The proposed methodology represents a major departure from general system identification methods whereby the functional form of the stress-strain behaviour is known. The algorithm is successfully demonstrated using synthetic and measured downhole array data. The results show that SelfSim is capable of extracting relevant cyclic material behavior from downhole array measurements. Ongoing research is utilizing SelfSim to extract soil behaviour from additional case histories and will examine in detail the extracted behaviour.

AKNOWLEDGEMENTS

This work was supported by the Earthquake Engineering Research Centers Program of the National Science Foundation under Award Number EEC-9701785; the Mid-America Earthquake Center. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation. The authors gratefully acknowledge this support.

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