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National Yang Ming Chiao Tung University
College of Engineering
Department of Civil Engineering

Application for NYCU Ph.D Elite Scholarship

Doctoral Program's Research Direction

Proposed Research Topic

Subsurface Seismic Velocity Profiling Using Deep Neural Network

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Motivation

Engineering problems are mostly viewed as the approximation problems, in which people try to find the possible solutions as near to the true solutions as possible and the optimization process involves minimizing the misfit function. The inversion problem, regarded as a very complex problem to solve, deals with uncertainty and non-uniqueness of solutions. The search on applying geophysical techniques to explore the geophysical parameters of the ground and then convert them to the geotechnical parameters for civil engineering application is large. However, the process of inversion is complicated dealing with various parameters and the uncertainty of the data caused by field conditions and human performance. One example is the dispersion of wave propagation in soil medium, there is not only one mode phase velocity dispersion curve, but multiple modes. The picking approach of dispersion curve has been considered to be highly objective, different people pick in different manners. The automated inversion algorithms are widely applied, but also very dangerous because of the complicated occurrence of higher-order modes and the argument of garbage in, garbage out.

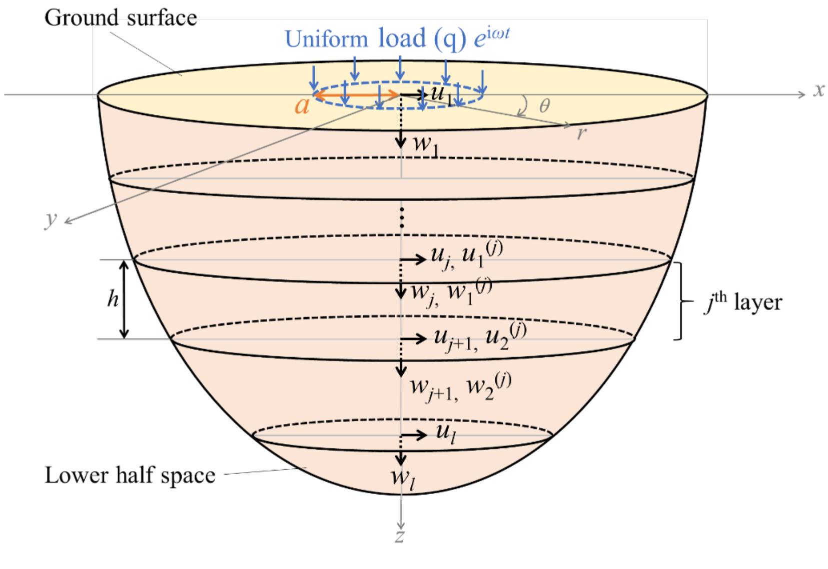

Figure 1: The coordinates and variables in a layered half space.

Although extensive literature review in this proposal is set in the next part, here after in this part will be an important description of the current research from Geo-Imaging and Geo-Nerve Lab (GIGN Lab) led by Prof. Chih-Ping Lin. The current research plays an important part in the proposed research topic. Thus, I would like to describe Prof. Lin's and his team's research in the introduction section.

The Geo-Imaging and Geo-Nerve Lab (GIGN Lab), where I belong, has done various research on applying geophysical methods to characterize the geotechnical engineering parameters. Currently, Prof. Chih-Ping Lin in GIGN lab and his research team are developing a more efficient model called Full-Wavefield Computational Model based on Fourier-Bessel Expansion (FBE) which is accurate and time efficient. The research on the new framework of full-wavefield inversion using the data from multichannel analysis of surface waves and the analysis based on Fourier-Bessel expansion, the framework is more time efficient compared to others' algorithms such as MultiSmart3D. The multi-layer model coordinate and model parameters are presented in figure 1.

From the results of Lin and his research team, the proposed model (FBE model) outperforms the modal summation method because the Full-wavefield inversion based on FBE is able to deal with near-field effects and leaky waves, while the modal summation is less accurate when dealing with those problems. The dispersion images with different modes (fundamental and higher modes) of the vertical and horizontal components of both the FBE and MultiSmart3D are shown in figure 2 and figure 3.

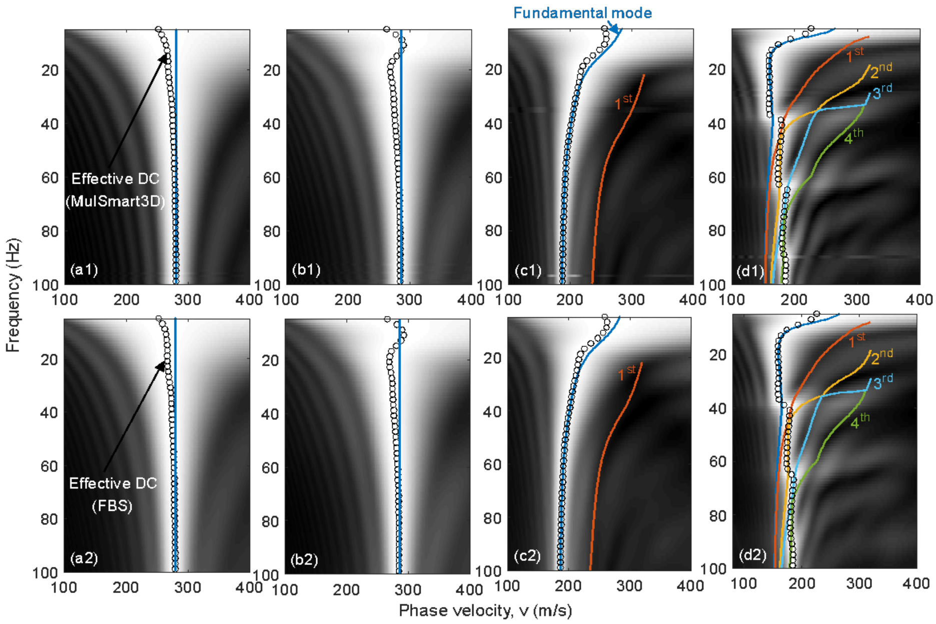

Figure 2: Dispersion images and dispersion curves of the vertical component signal from different models: (a) homogeneous half space (Poisson's ratio=0.33); (b) homogeneous half space (Poisson's ratio=0.48); (c) 3-layered model; (d) 4-layered model. Results from MultiSmart3D are shown on the top whilst those from FBS on the bottom. The solid lines in the spectra are the theoretical modal dispersion curves.

The research presented three pairs of shear wave velocity profiles to demonstrate the performance of full-wavefield inversion based on FBE shown in figure 4,5, and

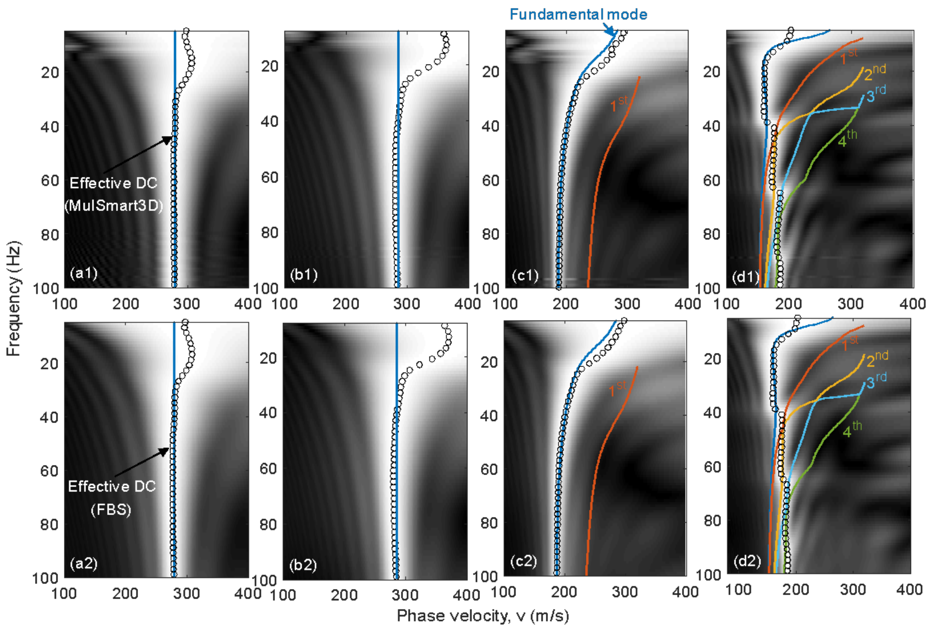

Figure 3: Dispersion images and dispersion curves of the radial component signal from different models: (a) homogeneous half space (Poisson's ratio=0.33); (b) homogeneous half space (Poisson's ratio=0.48); (c) 3-layered model; (d) 4-layered model. Results from MultiSmart3D are shown on the top whilst those from FBS on the bottom. The solid lines in the spectra are the theoretical modal dispersion curves.

figure 6. There are several parameters used as information to indicate the level of uniqueness for the sake of shear wave velocity profiles inverted such as model dispersion curves, effective dispersion curves and dispersion spectra.

Figure 4 indicates the distinct dispersion curve corresponding to the two different Vs profiles (profile A and B). There is one feature that is interesting which is that the fundamental mode dispersion curve in range of frequency from 15-40 Hz looks very similar, but their corresponding velocity files are entirely different. Nonetheless, from the frequency higher than 40 Hz, the relations between fundamental dispersion curves and Vs of two profiles are complicated and hard to explain based only on fundamental dispersion curves.

Figure 5 demonstrates the very similar dispersion curves (cases of profile C and D), but the similarity in the velocity profiles are just within 0 to 7 m. If looking deeper, the velocity profiles are very different or even contrast, while the dispersion images are nearly identical observed in both fundamental and higher-order dispersion curves. Another point is the observation of the velocity spectrum images, which may contain meaningful information at the certain parts (frequency and velocity regions). In other words, we may be able to extract more information by looking in batches of dispersion data. The profile E and F presents the similar dispersion images and also the similar patents of velocity profiles, which is the increase Vs magnates in proportion to the increasing depth. The different of Vs profiles of E and F are the different Poisson's ratio, in which (profile E has Poisson's ratio = 0.45 and profile F has Poisson's ratio = 0.3), the Vs magnitudes of profile F is close to that of E,

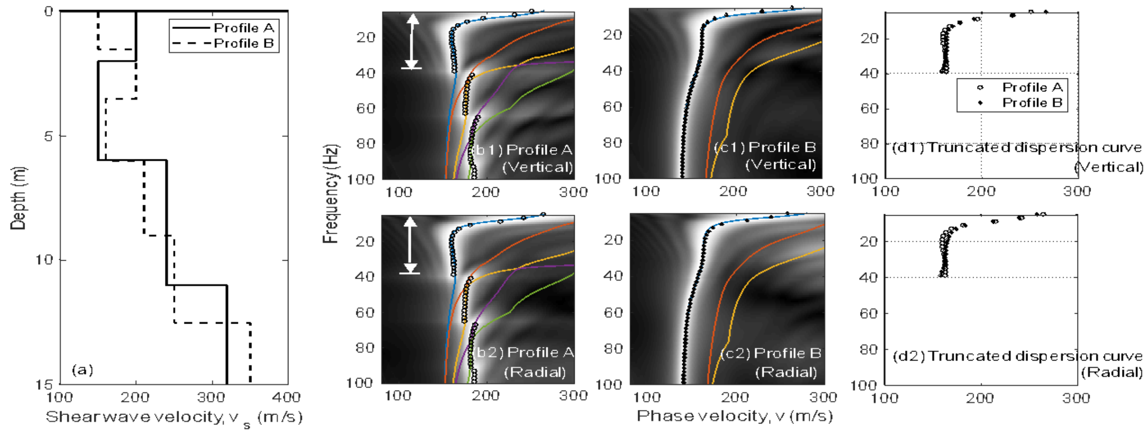

Figure 4: (a) The vs profiles; (b) the velocity spectra and effective dispersion curves of vertical component (top) and radial component (bottom) for profile A; (c) the velocity spectra and effective dispersion curves of vertical component (top) and radial component (bottom) for profile B; (d) comparison of the two fundamental-mode dispersion curves within the same frequency range for vertical component (top) and radial component (bottom). Lines in (b) and (c) are normal modes.

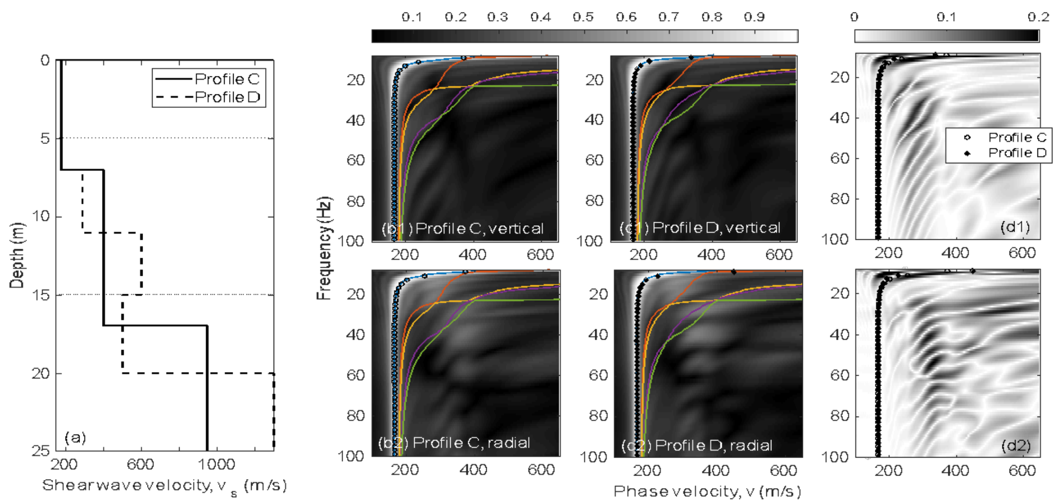

Figure 5: (a) The vs profiles; (b) the velocity spectra and effective dispersion curves of vertical component (top) and radial component (bottom) for profile C; (c) the velocity spectra and effective dispersion curves of vertical component (top) and radial component (bottom) for profile D; (d) comparison of the two effective dispersion curves and their velocity spectrum difference for vertical component (top) and radial component (bottom). Lines in (b) and (c) are normal modes.

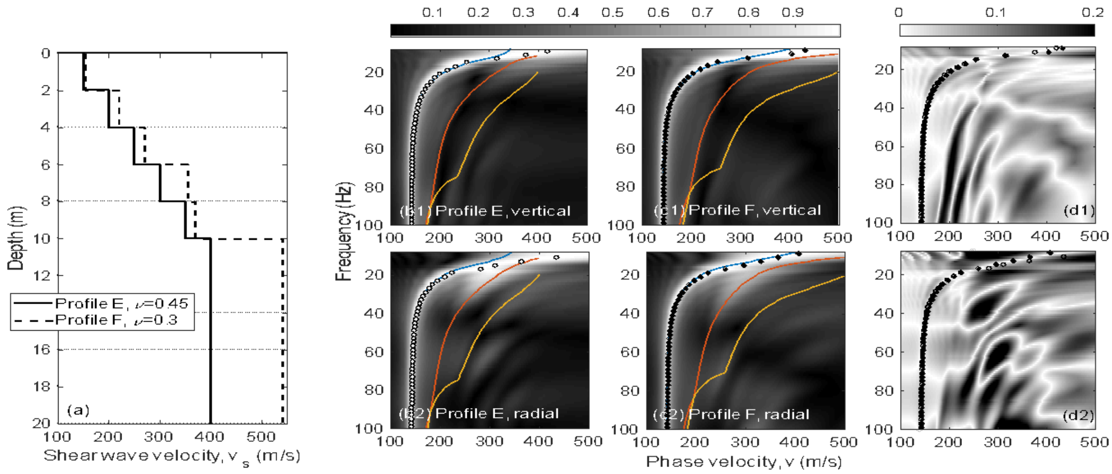

Figure 6: (a) The vs profiles; (b) the velocity spectra and effective dispersion curves of vertical component (top) and radial component (bottom) for profile E; (c) the velocity spectra and effective dispersion curves of vertical component (top) and radial component (bottom) for profile F; (d) comparison of the two effective dispersion curves and their velocity spectrum difference for vertical component (top) and radial component (bottom). Lines in (b) and (c) are normal modes.

but in higher depth, the Vs magnitudes of F is larger than that of E (from 10 m to deeper). Further observation is that the lower frequency effective dispersion curve is due to leaky waves (profile E), while the fundamental mode is dominant (profile F). Such that the performance fundamental mode inversion with respect to profile E may result in the overestimate in deep layer, the author suggested that making use of effective-mode inversion is much more appropriate than fundamental-mode inversion.

Because of the occurrence of different scenarios in inversion problems, one possible way is to try to extract more features from the data through power density spectrum in time or frequency domain, dispersion images or velocity spectrum and phase different spectrum, or other possible features. Figure 7 illustrates the radial-to-vertical spectral ratio between different profiles (RVSR) shown in top row and the radial-to-vertical phase difference of pairs of profiles (RVPD) shown in bottom row. The authors used the data at the middle receiver of 28 m offset. If we use data at all receivers, we may get the spectral images and those images may help to review much more meaning and explainable information.

Currently, the results still contain non-uniqueness (different earth models may have similar fundamental modes or the apparent dispersion curves). Because of that, additional parameters for interpretation of inversion results have been introduced which are the radial to vertical spectral ratio and the phase difference. The research shows that the framework is able to take the take and perform dispersion analysis and inversion efficiently. Beyond that, more constraints have also been introduced which are very helpful to use information of seismograms images, dispersion curve images, spectral ratio, full velocity spectrum as the input of an artificial neural network as input data, then through the network, the output is the prediction of the velocity profiles of the classification of different modes dispersion curves. The

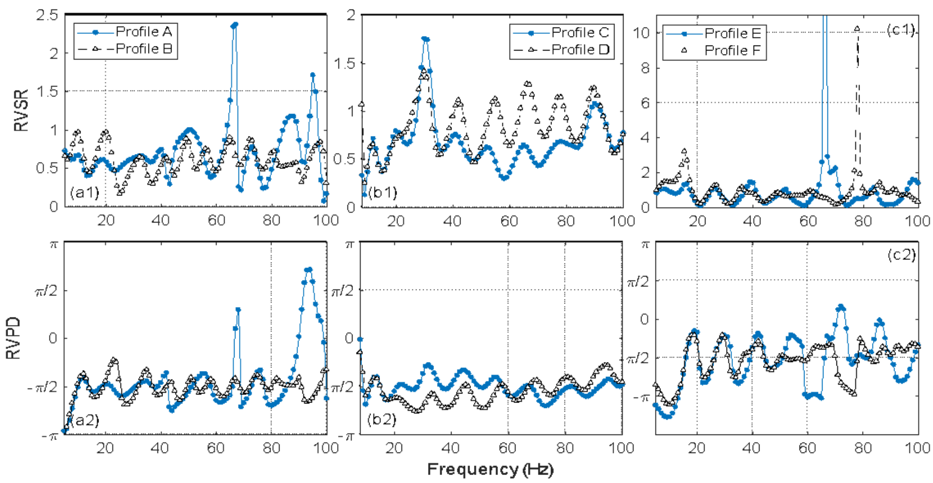

Figure 7: (RVSR (on top) and RVPD (on bottom) for the three pairs of cases at the middle receiver (offset = 28 m): (a) Profile A and B; (b) Profile C and D; (c) Profile E and F.

concept of learning from data (deep learning) is based on the use of data feeding into a certain model to predict the target, or machine learning which requires less data as inputs into a model constituted by layers with the final layer as the output. The idea of using a new concept of deep learning (a subset of machine learning) can be applied in the inversion process with the training data is the known output, the error is the difference between the predicted result and actual result. The deep learning model can be used to compare with the traditional inversion analysis.

Although the newly developed inversion techniques still have some limitations, it provides a large and meaningful data. The future works can be done to remove those limitations and make the inversion process more reliable and really help the non-destructive method be a great technique in solving engineering problems. Because of the very fast development of artificial neural networks, the powerful computer available and the capability to collect huge amounts of data. The most common deep artificial neural networks are the Convolution Neural Networks (CNNs) and the Recurrence Neural Networks (RNNs). The CNNs are very powerful working with images (classifications, predictions), while RNNs are applicable for sequential signals (natural language processing). Currently, there are various powerful deep learning models and machine learning algorithms are developed and those models are used in multidisciplinary subjects (astronomy, geophysics, economics, robotics, artists ...). The deep learning which is the combination of layers connected into a deep network with its parameters and hyper-parameters to take the input data and return desired output, the deep learning (DL) networks require much data, and the DL networks deal directly with input data. The machine learning (ML) models require manual manipulation of data (i.e., deal with the edges of images) then using the deep learning networks, usually require less data and there are plenty of ML models which can be combined to solve a certain problem. The DL networks are considered as a subset of ML, the ML models enable us to choose our own features, classifiers and training time with a small dataset. Both DL and ML are the cores of artificial intelligence (AI) models which come to perform tasks in the level far beyond what humans tell AI models to do.

From the observations of the power and the potential of ANNs to solve the inversion problems. Specifically, the inversion of the geophysical properties to the geotechnical properties, which is then applied in the field of geotechnical engineering. Nowadays, the geophysical test is very popular all over the world involving various engineering applications and the data collected from geophysical are very large, it is because geophysical tests involve seismic wave or the electrical current, enable engineer to perform test in the large scale and the data acquisition process is automatic, therefore geophysical engineers are able to acquire a large amount of data from geophysical tests. Taking the advantages of the huge dataset from geophysical tests and the available ANNs, DL, ML models, we may have a lot to do with the dataset and we may be able to interpret the data in a way that has never been explained in the past. The non-uniqueness of inversion problems and the essence of ANNs that motivate me to propose a research to solve the non-uniqueness phenomenon in inversion problems.

From above introduction, I would like to propose the new approach to use the available datasets and datasets from performing geophysical test, then apply different machine learning models to train the input geophysical datasets (geophysical parameters) and predict the engineering parameters (desire output). The model parameters (weights and inputs) and hyper-parameters (number of layers, learning rate, number of epochs, optimization algorithm, ...) are modified to explore the most applicable architecture of ML models. Also, the result of ML model will then be used to compare with the traditional inversion solutions to observe the performance of ML model with the conventional inversion algorithms.

The new point and also the most important aspect of this proposed research is the utilizations of conventional inversion (such as full-wavefield inversion approaches) to apply the artificial neural networks (such as CNNs, RNNs, and GANs) to further extract the crucial features or the insights of the data measured from the field (earth sub-layered system). The later part is to use the neural networks in order to perform the inversion tasks using the extracted features (not all features from large scale of data). The proposed research is expected to provide a new breakthrough and a complement to the current studies on earth sub-layered inversion problems with higher resolution and accuracy compared to previous studies.

Liturature Review

Inversion problems, recent solutions and limitations

The non-destructive test in sublayers identification as well as other size characterization purposes has been used for several decades. The non-destructive methods are cost effective and time efficient (Tomeh et al., 2006) such as spectral analysis of surface waves (SASW), multichannel analysis of surface waves (MASW), those methods are the most popular surface wave methods employing the properties of wave propagation of Rayleigh waves and Love waves in soil media (Kallivokas et al., 2013; C. P. Lin et al., 2017; C. P. Lin & Chang, 2004; Mahvelati et al., 2017; Park et al., 1999; Penumadu & Park, 2005; Xia et al., 1999).

The process of waveform inversion is to transform in-situ geophysical parameters into engineering parameters. Different techniques have been introduced for the inversion analysis such as first arrival method or dispersion curve approach. Dispersion is one of the important properties of wave travelling in solid medium, in which the relationship of angular frequency and the wave number is non-linear or different frequency components travel at different speeds (the group velocity component travels faster or slower than the phase velocity). Using the dispersion curve, the wave parameters can be used to transform to infer the layer profile. The inversion of geophysical properties of soil layers to the geotechnical properties known as inversion problems has been studying for many years and there are various inversion models proposed to invert the seismic wave field to the shear velocity profile and other geotechnical parameters such as horizontal to vertical spectral ratio (HVSR) (Deren Yuan & Nazarian, 1993; García-Jerez et al., 2016; Kallivokas et al., 2013; Leong & Aung, 2013; Luke et al., 2007; Moro, 2015b; Olafsdottir et al., 2020; Thorson & Claerbouts, 1985; Wathelet et al., 2004). The application of surface wave analysis for soil characterization is large such as ground improvement quality assessment, underground object detection, (Abudeif et al., 2019; Chris King et al., 1989; Sebastiano Foti et al., 2011; C.-P. Lin et al., 2012; C. H. Lin et al., 2017; Matthews et al., 2000; Tran et al., 2014).

However, the inversion problems are very complicated because of the uncertainties of the field conditions, data collection operations and many other impacts which contribute to make the non-uniqueness of inversion results (S. Foti et al., 2009; Roy & Jakka, 2017, 2018; Williams & Penumadu, 2011). The non-uniqueness of the inversion result is the reason making non-destructive surface wave methods be less reliable and conventional methods such as borehole tests, cone penetration test (CPT), standard penetration test (SPT) and other techniques. One of the common situations of non-uniqueness inversion is the occurrence of different shear wave velocity profiles of a certain inversion model or the similar shear wave velocity with the very different HVSR graphs. There are plenty of factors that influence the variation of the expected inversion results (nearest offset, geophone spacing, geophone spread length, field conditions, test equipment, testing time and other indicators).

A research on the use of middle-of-receiver-spread assumption of MASW method (Luo et al., 2009) indicated that the results of dispersion curves are very similar with the different nearest offset, and the dispersion curves are more likely to be different under the change of receiver spread structure. The above technique presents a method to explore the factors that are most likely to cause the non-uniqueness phenomenon in inversion problems. There are various indicators that cause non-uniqueness such as the data is inadequate, the complexity of site conditions, the coarse model characterization, or the model parameterization is not proper. A study on the inversion of seismic surface wave in case of complex profiles (Luke et al., 2007) presented a model to deal with a non-uniqueness problem adopting a two-step process, which is first optimizing model parameters by imposing searching boundaries, and then using the process of stochasticity with a large number of iterations to converge to the results with acceptable confidence level.

It is the higher-order modes that make uncertainty in choosing proper orders to invert. Therefore, many efforts aim to solve the non-uniqueness of inversion problems including the conventional inversion, the statistical, image processing, and neural network approaches. The interpretation of inversion results in very important, because the outcomes may not be used until one could properly explain his or her data and inversion model. In surface wave analysis, the results of inversion are usually the phase velocity profile, sublayer identification, compressional velocity profile (less common), the horizontal to vertical spectral ratio. The process of inversion is usually complicated involving data acquisition, dispersion analysis and the inversion techniques are applied. In the inversion problem, the introduction of parameterization and the use of standardization are very important to avoid the non-uniqueness of the inverted results. Nevertheless, the regularization and standardization of the use of geophysical test methods to apply to derive geotechnical engineering parameters are still quite limited, the international standards related to seismic tests are Cross-hole Method (ASTM D4428/D4428M-14, 2014), Downhole Method (ASTM D7400/D7400M-19, 2019), Seismic-Reflection Method (ASTM D5777-18, 2018), Seismic-Refraction Method (ASTM D5777-18, 2018), Geotechnical Borehole Geophysical Logging (ASTM D5753-18, 2018), the guide for selecting geophysical methods (ASTM D6429-20, 2020) and others.

The inversion problems involve three main works which are (1) field data acquisition; (2) dispersion analysis; and (3) inversion. There are various data acquisition techniques (Moro, 2015a). Generally, the general surface wave tests are the passive methods and the active methods, the dispersion analysis methods has been studying and different techniques have been proposed such as the tau-p transformation (George A. McMechan & Mathew J. Yedlin, 1981), f – k transformation, phase-shift method (Choon Byong Park et al., 1998) and the stacking method (Thorson & Claerbouts, 1985; Xia et al., 2007), and the image processing-based technique employing threshold energy filtering of the dispersion image (Taipodia et al., 2020). The use of two receivers to test and analyze the dispersion curve by SASW method is applicable and it takes the advantage of the large spreading, but it also has drawbacks related to the mode jumping in the dispersion curve images (Osama AI-Hunaidi, 1994). Other methods of dispersion analysis have also been studied with disadvantages and pitfalls, the attention on the multiple modes in dispersion analysis is much more common (Hayashi, 2012; C. P. Lin & Chang, 2004; Supranata et al., 2007).

Some studies pointed out that the properties of the dispersion curve may not only rely on the fundamental mode phase velocity of the dispersion curve, but also high modes phase velocity dispersion curves, which means that the different modes may contain the sublayers' information at different depths. The studies on using the combination of several modes of dispersion, the technique is so-called the effective dispersion curve of the apparent dispersion curve (Olafsdottir, Bessason, et al., 2018; Osama AI-Hunaidi, 1994; Subramaniam et al., 2020; Supranata et al., 2007).

Artificial neural networks and its applications in geophysical problems

There are also plenty of studies on the application of DL and ML in geophysical problems (Diersen et al., 2011; Guo, 2021; Liu et al., 2020; Peters et al., 2019; Ross et al., 2018; Wilkins et al., 2020; Zhang et al., 2020). A study on the P-wave arrival picking and the first motion polarity determination with deep learning (Ross et al., 2018) indicated that the automated algorithm for estimating the P-wave arrival has been less precise than the performance of human experts. However, dealing with a large scale, human efforts are impossible, therefore a CNNs has been proposed to use the datasets which are from the human experts' dataset (millions of pictures from experts' picking) and training the data for future prediction. The result indicated that the CNNs predict with the precision up to 95 percent compared to that of experts' picking data. A recent study on Automatic picking of multi-mode surface-wave dispersion curves based on machine learning clustering methods (Wang et al., 2021) proposed method of automatic picking method of multiple-mode surface wave dispersion curves employing an unsupervised learning approach. The 2D dispersion images are used as input data, clustering the dispersion energy and the background noise is performed. Then the multi-mode dispersion curves are identified by searching algorithm for local peaks, then the noise is removed by the particle filter. The results show that the automatic pick dispersion curves match the theoretical dispersion curves. The automatic pick dispersion curves are used in inversion problems and the result indicates an agreement with the borehole data.

Those above studies have demonstrated that the application of DL and ML are very powerful and potential in inversion problems. The results of previous studies have also presented that the use of DL and ML for inversion are well matched with the geotechnical test.

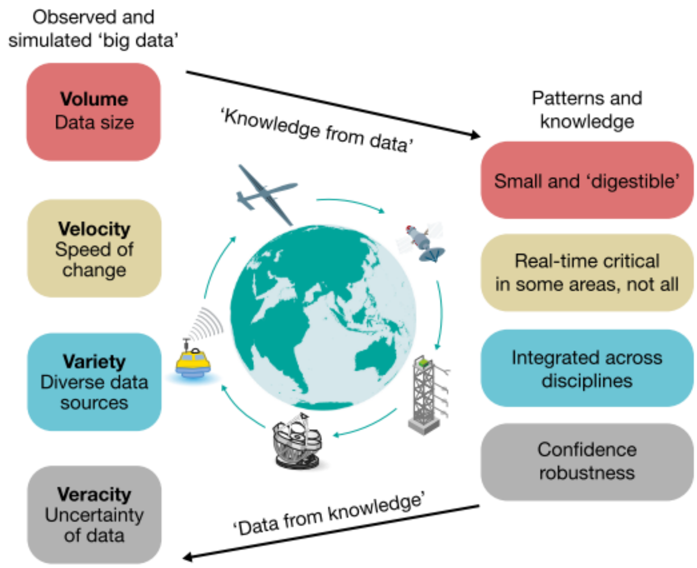

Figure 8: Big data challenges in the geoscientific context (Reichstein et al., 2019).

A research on Deep learning and process understanding for data-driven Earth system science (Reichstein et al., 2019), the study stated that machine learning approaches are developed and used popularly to extract patterns and insights from geophysical data. In the paper, it is argued that the deep learning approach should be employed rather than the classical machine learning, such that the approach enables automatic extraction of special features to gain more understanding of the earth system, improving prediction ability and interpretability of earth structure.

Figure 8 presents the big data involving the concept of "four Vs", including volume, velocity, variety and veracity. The key is to overcome the challenges of the capability of extracting the interpretable information and the knowledge from big data. Unfortunately, our ability to collect and create data outpaces our ability to properly interpret it. The capability to explain the data over the last few decades has not been at the same rate with the data available. It has been recognized that, to get the meaningful part from big data, we may need to cope with two main tasks, which are (1) to extract the knowledge from data, and (2) building models that learn from the data much more from the traditional data assimilation approaches, but still respect the nature's law.

Although the intensive studies and widely sheared deep artificial neural networks, the similarity between the traditional machine learning and applied machine learning in the field of geophysics is striking, but still need a lot of works need to be done to really understand and apply properly machine learning in the field. The examples of the similarity between traditional machine learning model and the use of machine learning in the field of geophysics are shown in figure 9, the linkages between the physical models and machine learning is abstractly illustrated in figure 10.

A study on a deep residual network of convolution and recurrent units for earthquake signal detection (Mousavi et al., 2019) that makes use of combination of convolution layers and bi-directional long-short-term memory units in a residual structure. The

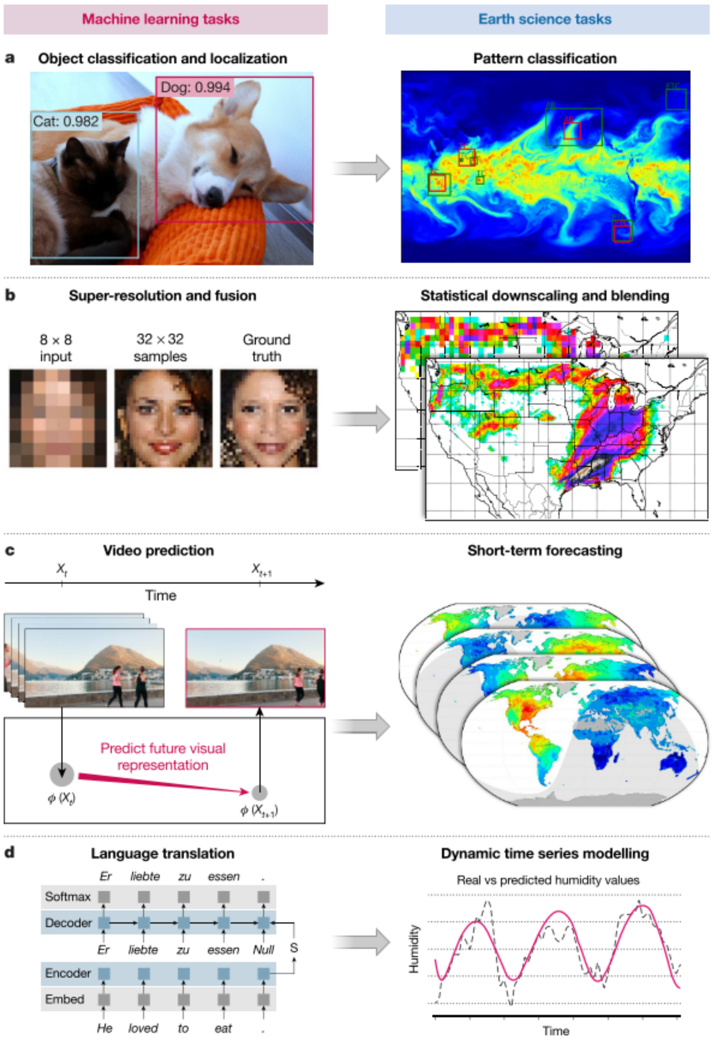

Figure 9: Four examples of typical deep learning applications (left panels) and the geoscientific problems they can be applied to (right panels) (Reichstein et al., 2019).

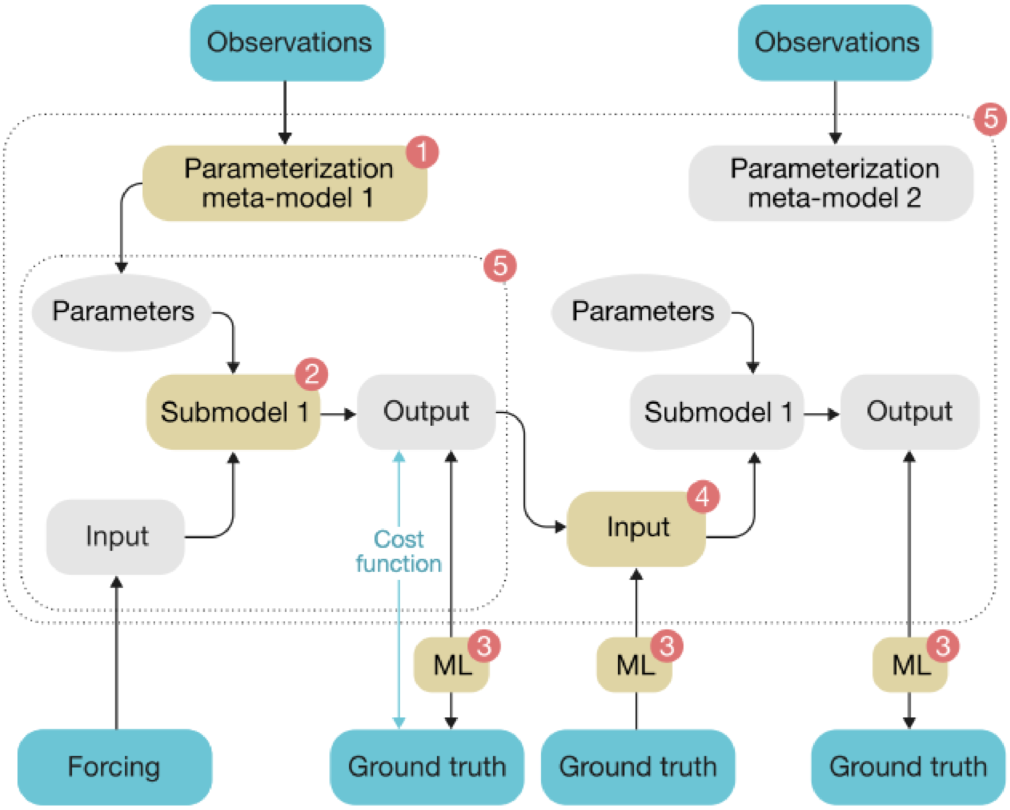

Figure 10: Linkages between physical models and machine learning

model learns from the time-frequency properties of earthquake signals of three component data with different station data collection. The network is trained with 500, 000 seismograms taken in Northern California. The network architecture is shown in figure 11, which includes four main parts (1) seismograms input, (2) feature extraction, (3) sequential learning, and (4) classification.

The architecture of the network is presented to include three types of layers: (1) convolution layers, (2) recurrence layers, and (3) and the fully connected layers. The description of the training and testing data dataset is that there is 80 percent data for training, 10 percent data for validation and the final 10 percent is the testing data. The optimization model used is Adam, the number of epochs is 62.

The results of the previous study indicated that the proposed network is reliable and efficient, the framework has the great expectation for reducing the detection threshold while minimizing false passive detection rates.

Problem definition

Although various conventional inversion models have been introduced and used wildly all over the world, people are still facing the uncertainties and non-uniqueness of the data and inverted results. The use of such an inversion model may need a lot of evaluations and judgements of experts who have much experience dealing with

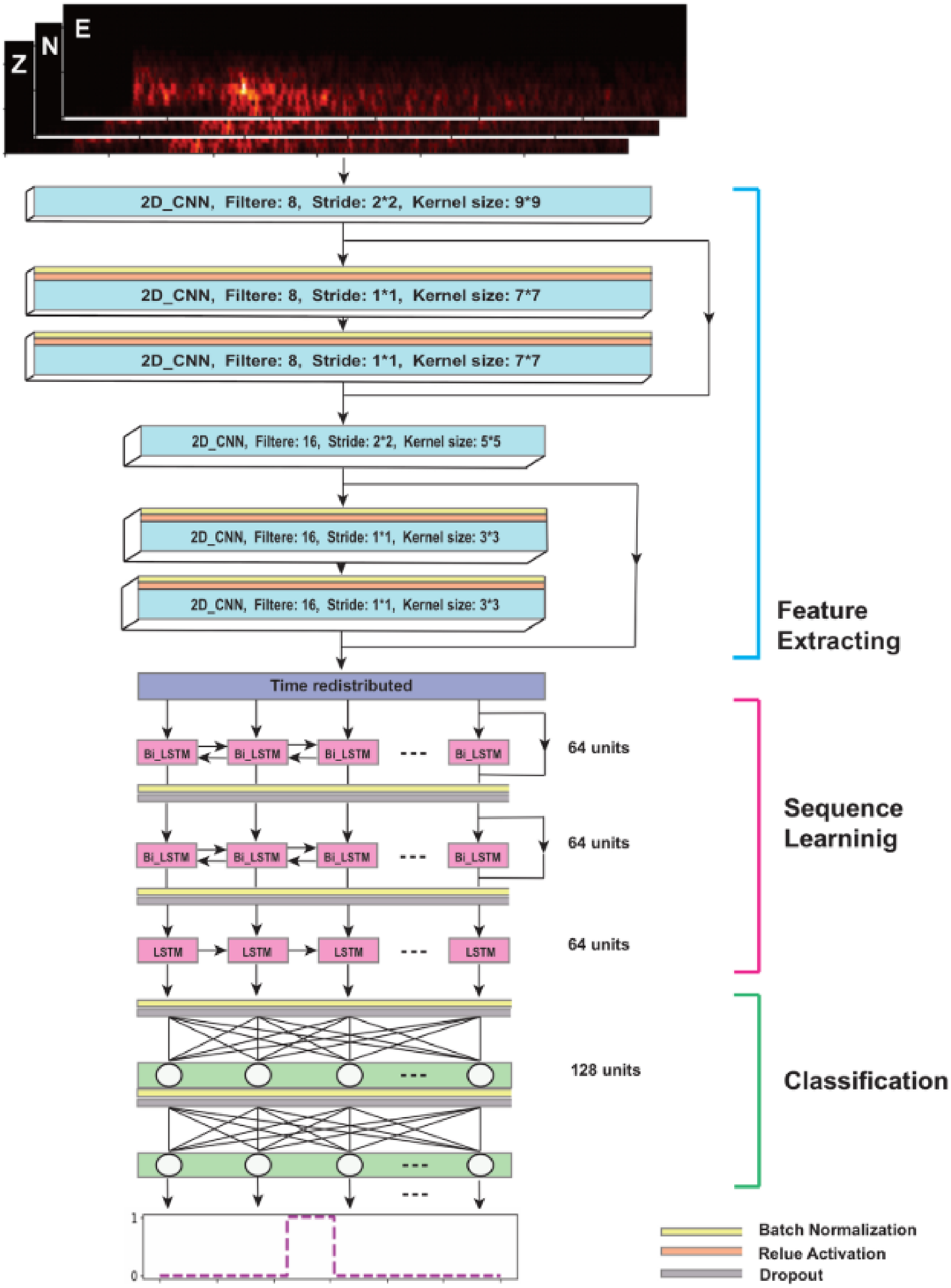

Figure 11: The architecture of our proposed deep neural network (Mousavi et al., 2019)

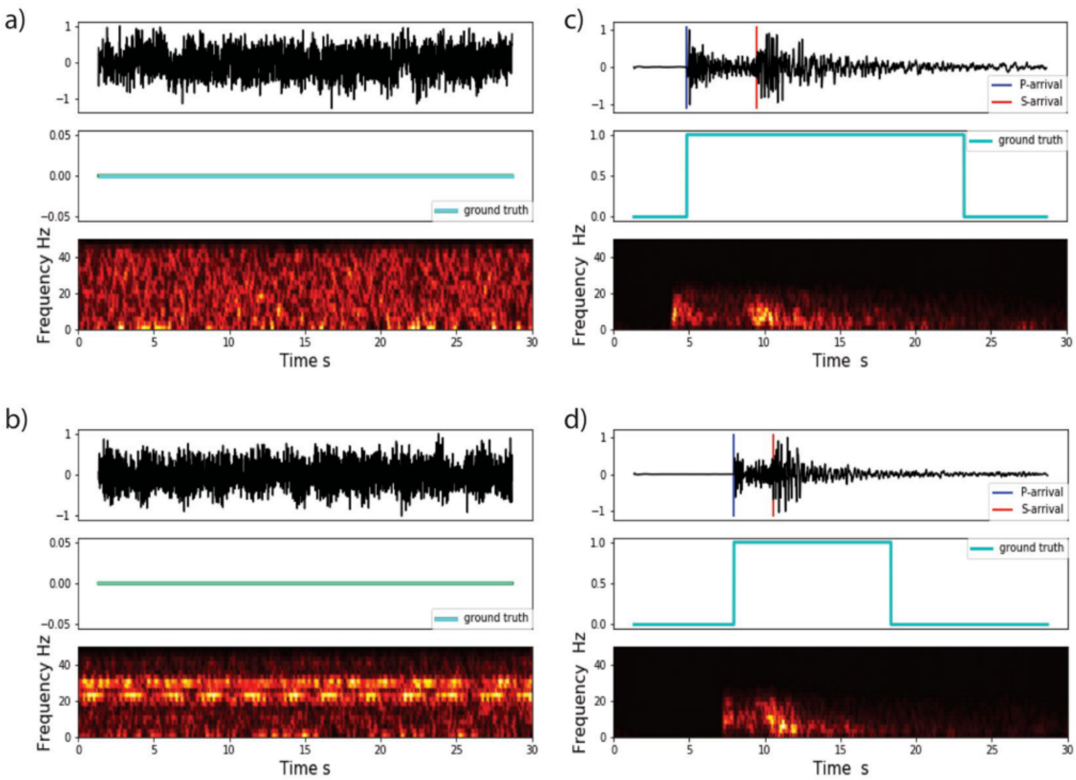

Figure 12: Examples of seismographs, label vector, and associated spectrogram (short time Fourier transform, STFT) for vertical components of two sample noises (a,b) and two earthquake samples (c,d) (Mousavi et al., 2019)

inversion problems.

The recent development of waveform inversion approaches brings to engineers many beneficial aspects. Because the conventional inversion process inevitably produces a lot of information, such as measurement of waveforms should be fully utilized to maximize the information content for inversion (i.e., full waveform and holistic approach). Those can be the data for the artificial neural networks (such as RNNs, CNNs, and GANs). The information extracted from the conventional inversion approaches can be full-wavefield seismograms, pre-processed wavefields, dispersion images, spectral ratio (HVSR, HVPD). As we have more information, we may be able to improve the resolution and accuracy of inversion results (such as velocity profiles, Poisson ratio profiles).

One more problem that we may face when dealing with conventional inversion is time consuming. Some models require much time to process. Utilizing neural networks means that machine learning and deep learning will play the role of extracting necessary information. Thus the quantity of data can be reduced, but still contain much meaningful data.

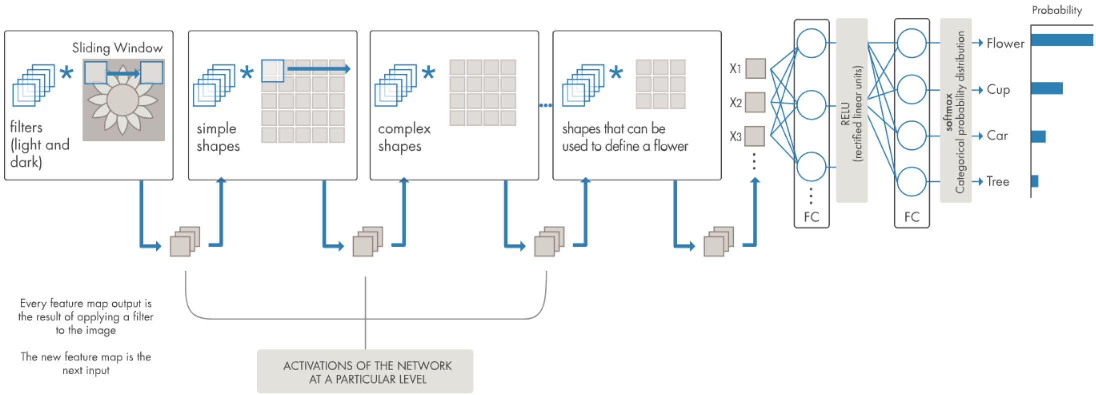

Figure 13: Illustration of a CNN (courtesy of Mathworks)

Proposed methodology

The method we propose is the application of a neural network, we would like to call it the inversion neural network. This method requires data for training the network to let the network learn to extract the features of input data which are the dispersion images, images of spectral ratio and other data from pre-processing stage. In this stage, we need to find a good automated inversion method to generate data for training later. The conventional inversion methods are used and compared and we will need to choose a specific inversion technique that is more robust.

The idea of inversion-based images is the use of data from realistic numerical models and treated them as images, then data in form of images will be the input vectors of the ANNs (Convolution Neural Networks, Recurrence Neural Networks, Generative Adversarial Networks or other new developed networks). The whole data is generally divided into three parts (training data, validation data, and test data), the training data and validation data are involved first and the test data involved in the end. The training process consumes most of the time (it is like human learning process), after each cycle of training, the validation data will come to evaluate whether the training data is good or not (this is based on the accuracy and the error cures). After training, the prediction will come to predict the new data (test data) based on the trained data. An example of CNN architecture is shown in figure 13, the figure is taken from the Mathworks.

The network initialization (input, initial weight, initial bias), architecture and other hyper-parameters (number of nodes, number of layers, activation functions, gradient descent scheme, number of epochs, . . .) are defined by the one who is working with it. The model is designed to consist two parts, the first stage is manually extractions of objective features from the data using Machine Learning algorithm available and the second stage is the fully connected network with a set of layers (input layer, convolution layers, pooling layers, classification layers, fully-connected layer, Softmax layer, . . .) and activation functions figure 14 (Linear, ReLU, Sigmoid activation functions).

After the classification or prediction is done, the test data is involved to measure the misfit of the prediction, the test data is considered as the true answers (or

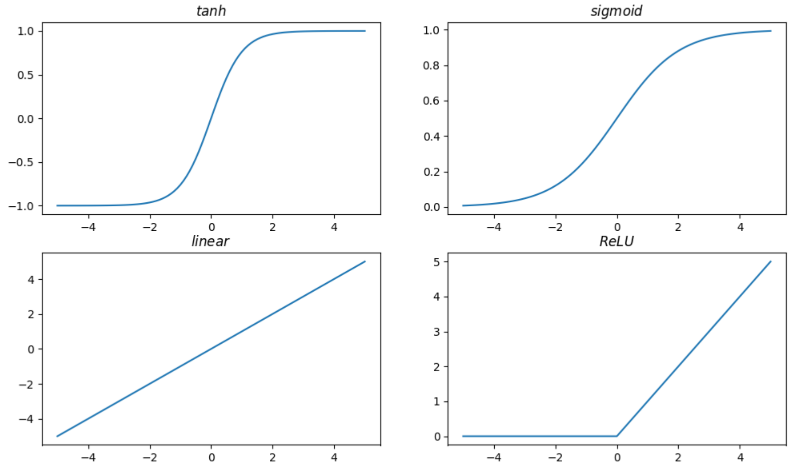

Figure 14: Some of popular activation function

the expected ground truth), then after error evaluation, the model will adjust its parameters to improve the performance based on the very famous method of "back-propagation" employing available algorithms (Stochastic Gradient Descent (SGD), SGD with momentum, Adam, RMSProp, . . .).

Because the problem has unknown ground truth in nature. It is different from the popular faces, hand-written digits or objects recognition problems which were studied several decades ago and still popular recently. We do not know yet the true answers, the real data will naturally come from the traditional geotechnical field test (borehole samplings, in-situ subsurface parameters exploration), geophysical explorations (cross hole, down hole, surface wave methods, and even electrical methods), and data are then pre-processed, processed using developed numerical models to extract the information from the raw data. From those extracted features (such as dispersion curves of horizontal/radial and vertical components, RVSR, RVPD and other field data that are applicable).

Figure 15 illustrates the overview of the MASW method (Olafsdottir, Erlingsson, et al., 2018). The data is collected and the presentation of data in form of seismograms, the dispersion curve analysis and the inversion.

The data collection from available sources and the field acquisition data are used for both conventional inversion problems (concentrate on full-wavefield inversion) and the artificial neural networks (concentrate on convolutions neural networks). The data used in conventional inversion and CNNs are from the surface wave test (MASW).

Pre-processing (i.e., remove mean, data normalization) may be necessary, the data input of CNNs are dispersion curve or spectral ratio of horizontal and vertical velocity components. The dispersion analysis is required; the extraction of fundamental mode dispersion curve or higher-order dispersion curves is used for the input of the inversion process. In CNNs model the data is divided into three parts, which

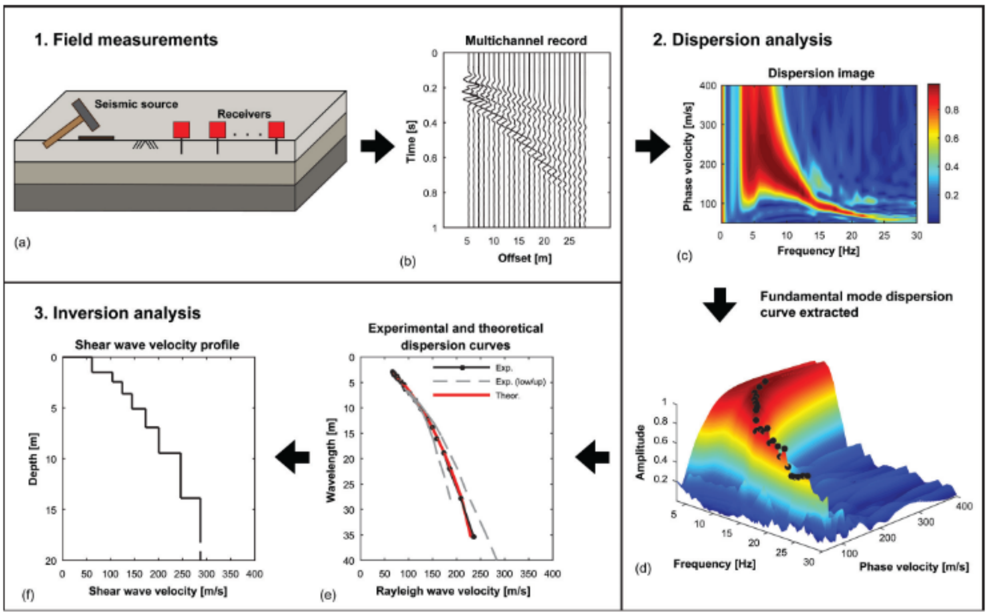

Figure 15: SOverview of the MASW method: (a, b) field measurements; (c, d) dispersion analysis; (e, f) inversion analysis (Olafsdottir, Erlingsson, et al., 2018)

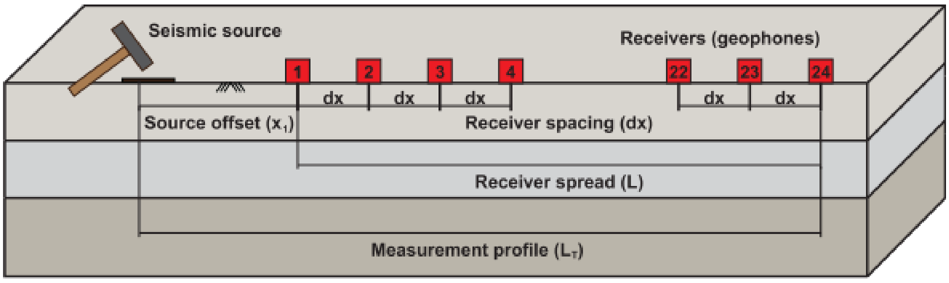

Figure 16: Typical MASW measurement profile (Olafsdottir, Erlingsson, et al., 2018)

include: (1) Training data; (2) Validation data; (3) Test data. The proportion of each part is selected based on the suggestion of previous research or can be chosen randomly with the higher proportion of training data (around 80 percent) and lower proportion of validation (around 10 percent) and test data (around 10 percent). The performance of conventional inversion process involving three main parts, which are: (1) data acquisition; (2) dispersion analysis; (3) inversion. It is very crucial to notice that we do not have data at hand, we need to prepare the fairly large amount of data for training the network. The proposed training information is the dispersion images, feature images (horizontal-to-vertical spectral ratio images) and the shear wave velocity profiles (labels). To have this data, we need to have a inversion algorithms that can automatically perform inversion analysis that are reliable and need to be validated with other proposed algorithms. Once we have the data set at hand, we then could be able to use it the training the inversion networks. This is considered as supervised learning approach.

There are some algorithms that are considered to perform the inversion, they are framework of full-wavefield inversion based on the Fourier-Bessel expansion, fast

(a) Testing field

(b) Mini hammer

(c) Small hammer

(d) Big hammer

Figure 17: Illustrations of testing location and sources types

inversion (Cao et al., 2011), simplified inversion (Pelekis & Athanasopoulos, 2011). The CNNs also involve three main parts, which are (1) data input; (2) training data and (3) prediction

The input or input layer will be the image dataset from numerical models including dispersion curves, RVSR images, RVPD images shown in figure 19 and figure 20.

An illustration of field data acquisition as an example of data collection. The test was taken in the Softball field located at National Yang Ming Chiao Tung University, survey length is 23 m. The geometry design of the field test Figure 16, the testing location and types of hammer (impulse generators) are shown in Figure 17, the testing information and field description are presented in table 1, the synthetic seismograms are presented in figure 18.

Table 1: MASW Experiment parameters

*8X[c]

2*Parameters Dimension

Types Mini Small Big Mini Small Big

$X_0 m$13101310

$\delta x m$111222

Stacking Times 5 3 4 5 3 3

ID - 3237 3240 3239 3242 3241 3243

Name - V(mini) V(small) V(big) V(mini) V(small) V(big)

Name - ch10,flip ch10,flip ch10 ch10 ch10 10,flip

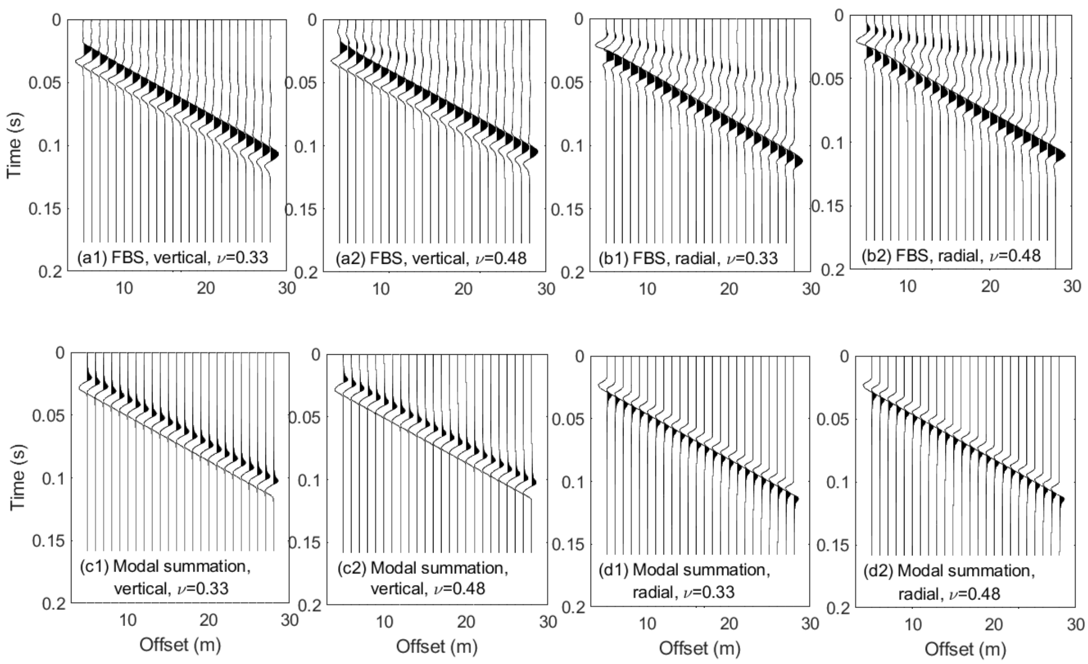

Figure 18: Synthetic seismograms of the homogeneous model with different Poisson's ratio Poisson's ratio using the FBS approach (top, (a) for vertical and (b) for radial component) and the modal summation method (bottom, (c) for vertical and (d) for radial component). (Courtesy of Lin and his reesarch lab)

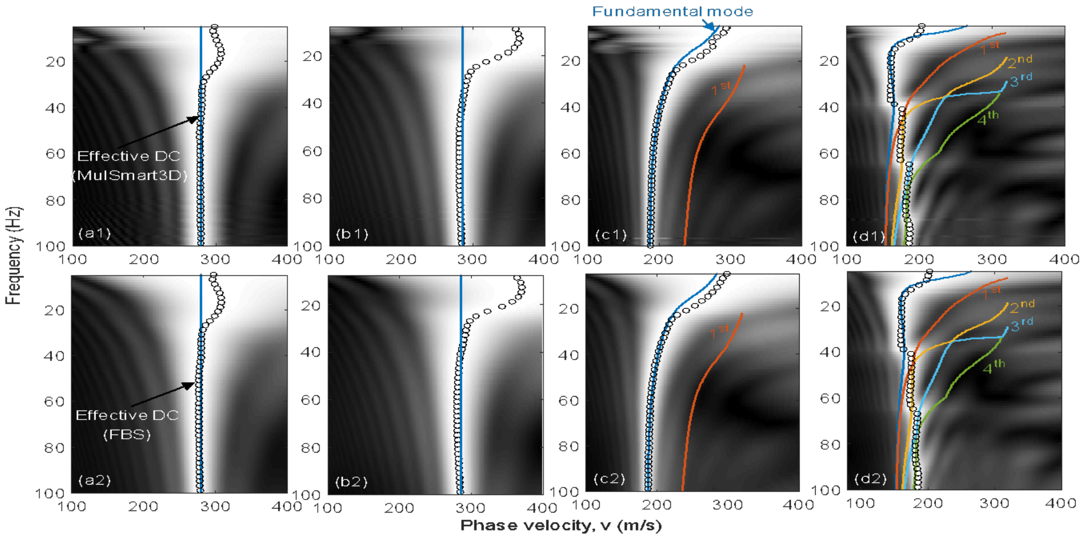

Figure 19: Look at dispersion images as input data (seismic features)

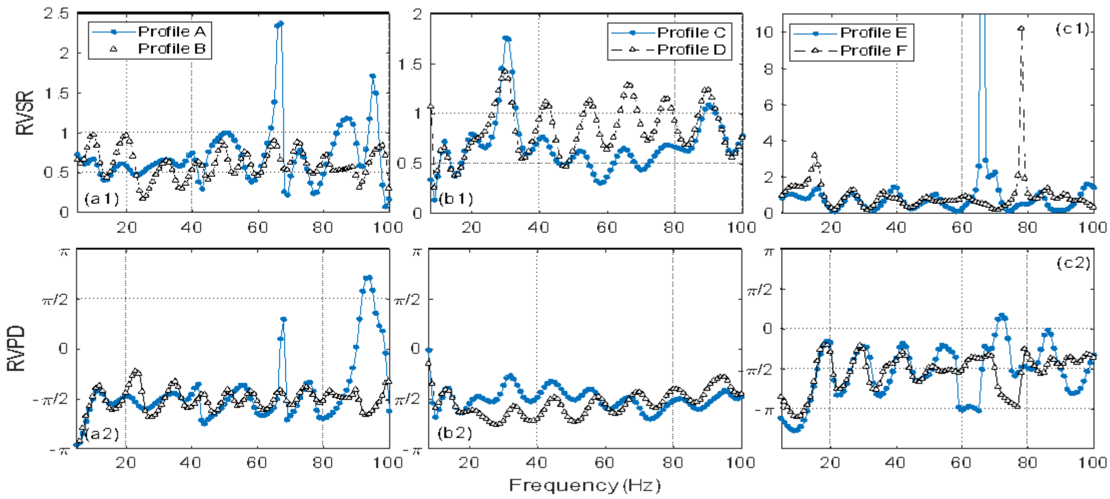

Figure 20: Look at SRVSR and RVPD as input data (seismic features)

The network hyper-parameters are chosen and adjusted to find the most appropriate network architecture for the performance of prediction, and avoid problems such as being stuck in local minima, overfitting or underfitting. The performance of both conventional inversion and inversion applying CNNs are judged and compared.

Expected results

Different ANNs could be employed in this research, the CNN is the one that is mostly focused on because of its power in imaging problems. The expected results of inversion from different models are discussed.

We will try to find the solution of inversion that provides the high reliable results which is the tool to create data for the neural network inversion process. The data input for model training will be tested and validated carefully. During this process, the model parameterization and regularization will be involved.

This proposed research topic aims at a new view point in the solution of inversion problems. The CNNs are expected to outperform the conventional inversion in terms of prediction of shear wave velocity profile which is widely used in engineering applications. The

The inversion using CNNs is also expected to provide engineers more interpretation capability of the geophysical data based on the learning process and the extraction of information of the neural networks. The CNNs are expected to provide a tool for prediction of geotechnical parameters by the input of geophysical parameters. So that, we may be able to have more information for the explanation of inversion results all together with conventional inversion models (Dimililer et al., 2021).

Future work

In the current proposed, I plan to figure out the framework of using inversion neural network to invert the geophysical data to geotechnical information, the information will then be evaluated on its applicability in engineering practice. In the future, I also would like to put my effords on the adjustments and enhancements of the inversion neural network to make it more interpretable and applicable in solving the inversion problems.

Network optimization is also a very important aspect, once the framework of inversion neural network is constructed and evaluated. The network optimization needs to be studied in order to improved the performance of the network.

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