ESTIMATION OF SHEAR-WAVE VELOCITY PROFILES IN PERU BASED ON MACHINE LEARNING ALGORITHMS

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Abstract

It is well-known that the configuration of the stiffness of surficial soil stratigraphy plays an important role in the evaluation of seismic intensity and, therefore, its accurate evaluation is crucial. In this regard, seismic methods based on the propagation of surface waves are one of the most commonly used techniques due to its relatively low cost and high reliability. Processing the generated signals in the frequency domain allows the calculation of the characteristic dispersion curve of phase velocities of the soil medium. The subsequent application of inversion techniques makes possible the final estimation of shear-wave velocity profiles, whose theoretical dispersion curve fits, with a minimal achievable error, those obtained in field surveys.

Several methods have been adopted for the inversion process mainly based on the linearization of an inherent non-linear multi-parameter problem. This type of approach has the disadvantage of intrinsically depending on the initial model and likely falling in a local minimum. To overcome this problem, this study considers the development of a new approach of inversion by means of modern optimization methods based on machine learning and convolutional neuronal networks. Thus, the development of an intelligent system which learns the intrinsic relationships between soil profiles and their corresponding dispersion characteristics of the propagating surface waves is proposed. For the calibration process, 90 % of the database is conceived to be used, whereas the evaluation is conducted for the remaining 10 %. Preliminary computations based on the generation of 1000 random soil profiles up to 30 m depth exhibit significant agreement between theoretical and estimated dispersion curves.

This study is conducted within the framework and financial support of the Concytec – The World Bank “Improvement and Extension of the Services of the National System of Science, Technology and Technological Innovation” Project 8682-PE, through its executive unit Fondecyt (contract 038-2019).

Keywords: Inversion; convolutional networks; dispersion curve; shear-wave velocity profile; machine learning

1. Introduction

Within the framework of the project "Enhancement and Extension of the Services of the National System of Science, Technology and Technological Innovation" 8682PE, specifically the subproject "Fusion of Machine Learning Algorithms and Earth Observation Technologies" [Contract 038-2019], the implementation of a system that under the occurrence of an earthquake generates its corresponding seismic intensity map is currently being implemented. In this context, an overall understanding of the behaviour of seismic waves at the engineering bedrock in Lima, Peru, is being sought as well as the effects of the overlying layers for the motion observed at surface [1].

During the aforementioned study, it was observed that traditional procedures used to identify the distribution of the dynamic properties of soil deposits have significant limitations that might be improved through modern techniques such as machine learning. Due to the relevance of the study, and not only within the context of the project 038-2019 but also future applications in the industries of construction, geotechnical engineering and urban planning, this study presents promising results in the utilization of convolutional neuronal networks as an alternative in the accurate identification of shear-wave velocity profiles.

2. Dynamic Properties and Field Methods

2.1 Phase Velocity Dispersion Curves

As consequence of the propagation of seismic waves, strain energy is transmitted, in first instance, in all directions and by what is known as body, P and S, waves. Once these waves reach the surface of the medium in which they propagate, their polarization mechanism is altered and transformed into surface waves (Rayleigh and Love). Geophysical seismic tests make particular use of this type of waves since, by means of their recordings, is possible to infer the soil substructure in which they propagate.

One of the most important characteristics of surface waves is their dispersion in a multilayered media, i.e. low-frequency (long period) waves propagate with larger velocity values than those with higher frequency (short period). This specific detail has a major impact in the investigation depth since shorter wavelengths allow surficial exploration whereas, with longer wavelengths, the estimation of the deeper substructure is achievable. Thus, the curve that synthetizes the distribution of the frequency of a particular surface wave and its corresponding phase velocity is called dispersion curve.

The importance of obtaining an accurate dispersion curve lies in that, by means of adequate techniques of inversion and optimization of the solution, is possible to infer the soil substructure in the form of shear-wave velocity profiles (Vs). These profiles are the main parameters of an adequate evaluation of site effects that might lead to the identification of the amplification of seismic energy for certain period range.

2.2 Multichannel Analysis of Surface Waves Tests

Among the most disseminated geophysical tests, Multichannel Analysis of Surface Waves (MASW) arises as one of the easiest with respect to its field implementation. This type of test considers the deployment of a number of vertical component sensors (velocimeters), 12 or 24 in the most common configurations, along a line [2].

This type of test contemplates the multichannel record of the vertical components of Rayleigh waves that propagate along the underlying stratification under the seismic line caused by an active source (Fig. 1 a, b). In the majority of the cases, this active source is generated by a hit of a 10 kg-sledgehammer on a metallic plate at certain distances from one of each sides of the seismic line, in order to obtain a wavefield containing mostly surface waves since body waves, which are those generated first, rapidly attenuate with distance. Thus, processing the generated multichannel time-history records by techniques in the frequency domain, such as f-k (frequency-wavenumber), allows the isolation of surface waves. Thus, a normalized velocity spectrum is obtained, where the regions with highest energy represent an image of the dispersion curve of phase velocity for the propagated Rayleigh waves.

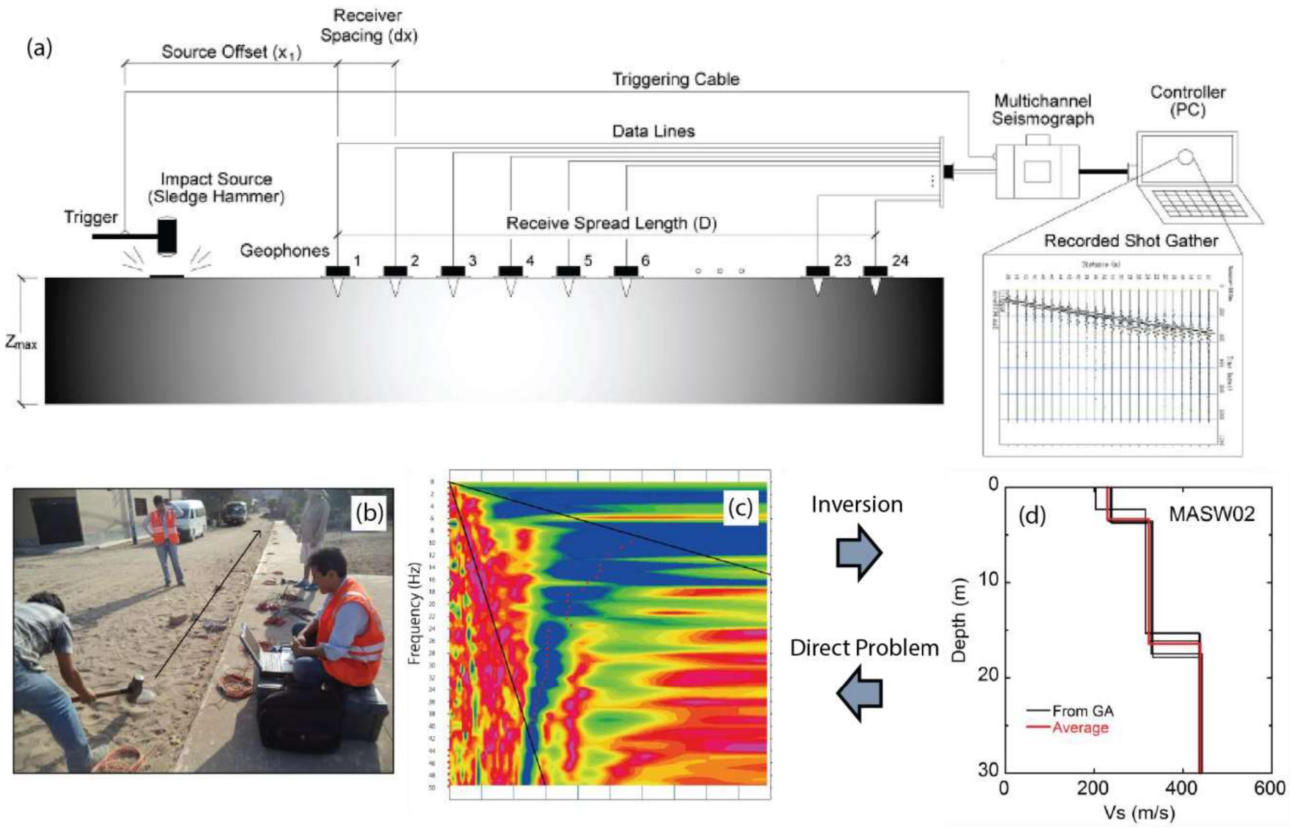

Fig. 1 – (a) MASW equipment configuration, (b) MASW field survey, (c) dispersion curve, (d) shear-wave velocity profile

Hence, the obtained dispersion curve is an intrinsic property for a given stratigraphic configuration, which can be calculated by means of a matrix procedure, such as Haskell-Thompson methodology, being this type of problem called direct problem [3]. In a real context, the opposite situation occurs, in which from the field information, the corresponding dispersion curve is generated, that can be referred as the consequence. Therefore, the analysis is performed towards the estimation of the shear-wave velocity profile that causes such dispersion pattern. This is the basis of the so-called inversion problem (Fig. 1 c, d).

In general, the reliable exploration depth that can be reached with this type of tests is about 30 m, which agrees with that required for the site classification of soil deposits in the majority of seismic codes utilized worldwide [4, 5], being this one of the main reasons why this technique is so widespread. Other techniques, that take under consideration the analysis of ambient vibrations (microtremors), allow the consideration of longer wavelengths and, therefore, the estimation of a deeper soil substructure [6].

3. Database

In general, machine learning techniques require a considerable amount of training and evaluation data. Unfortunately, and in the Peruvian context, there is scarce and limited information regarding real data of MASW tests, since its compulsory application in the local seismic code is only recently specified. In order to overcome this limitation, synthetic shear-wave velocity profiles were generated with the objective of contributing to the further performance and application in real cases, once the neuronal network is calibrated. The discretization of each of these synthetic profiles considers a thickness of 2 m for each of the soil layers, according to the typical resolution that a MASW test would produce. On the other hand, and with the objective of preliminary evaluating the suitability of the methodology for engineering practical cases, 15 soil layers were generated down to a depth of 30 m.

Based on the geomorphological characteristics known for typical deposits in the city of Lima, Peru, and the increase of the confining pressure, the decision of generating synthetic profiles whose stiffness, in the most probable case, increases with depth was taken. Taking soil deposits in Lima as reference, and according to the experience with geophysical tests carried out in the city, the value of the shear-wave velocity of the topmost layer was considered to vary randomly from 150 m/s to 350 m/s. For the deeper structure, their shear-wave velocity values represent a percentage of the velocity of the corresponding layer immediate above, being this percentage randomly lying within 97.5 % and 125 %. Fig. 2 shows a sample of 10 profiles of the total of 1000 generated.

Then, by means of algorithms related to the estimation of phase velocity for Rayleigh waves solved for different modes of vibration in a perfectly elastic, isotropic and laterally homogeneous medium, dispersion curves were obtained for the synthetic profiles generated [7]. Specifically, phase velocity values were calculated for 1000 frequencies within the range of 0.1 Hz and 1000 Hz.

4. Convolutional Neuronal Network

A typical neuronal network consists in three main layers: (i) convolutions, (ii) pooling and (iii) lineal combination (Fig. 3) [8, 9]. In the present study, input data was represented as a vector of 1000 components describing a unique dispersion curve. The first layer consists of 16 convolutions applied to this type of data, generating a 1000 x 16 matrix, which is later normalized in such a way that each column has an average equal to zero and a unit standard deviation. Finally, the activation function is applied to each element of the matrix. In this case RELU activation function (Eq. 1) was used:

$$RELU(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases} \tag{1}$$

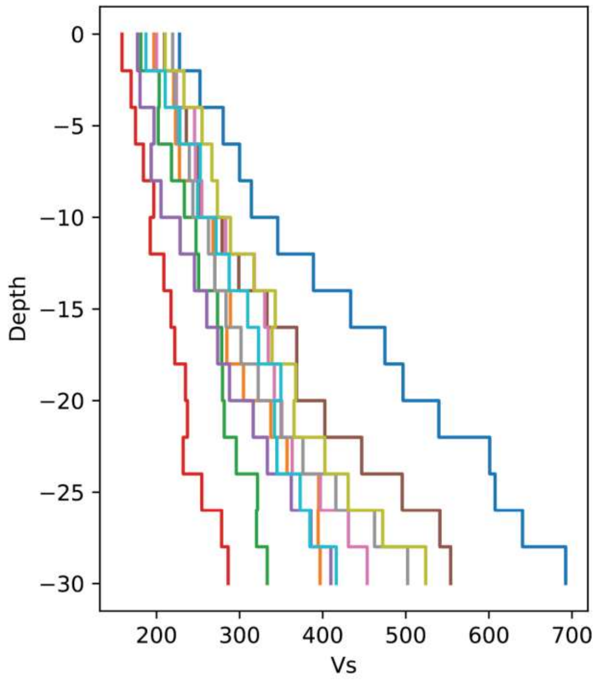

Fig. 2 - 10 of the 1000 synthetic soil profiles generated for the calibration and evaluation of the effectiveness of the proposed neuronal network

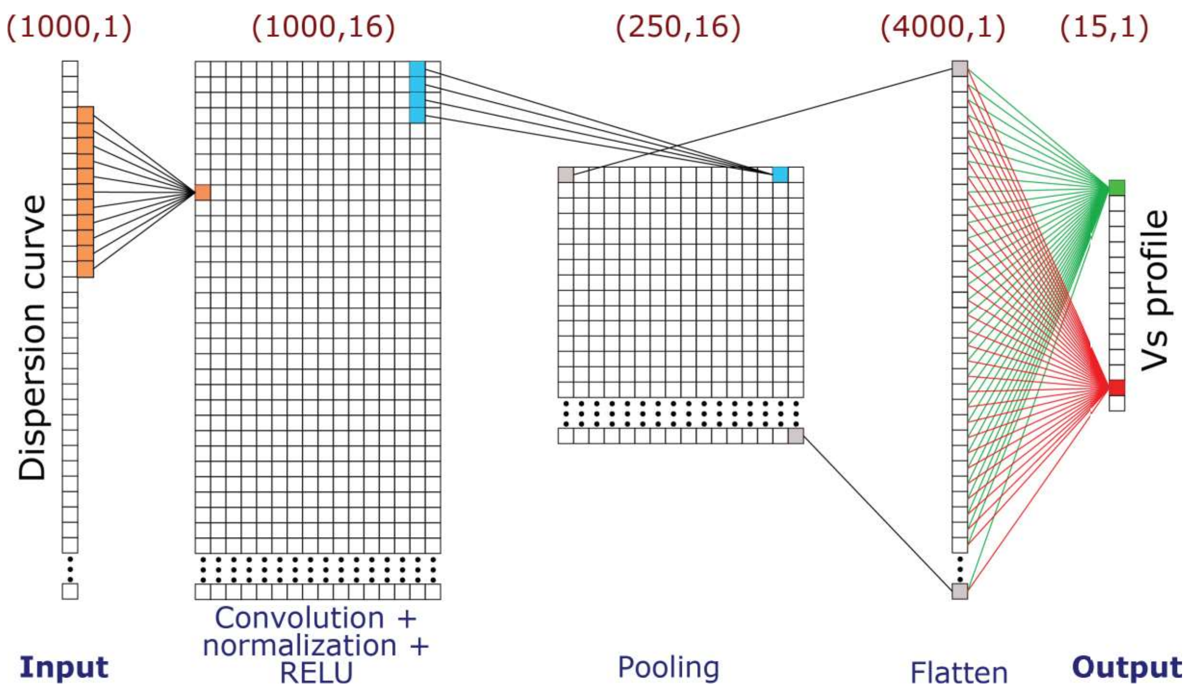

Fig. 3 – Architecture of the neuronal network

The second layer consisted of a process named pooling, in which, for every column, each four components are reduced to one with the objective of avoiding redundant information resulting from the convolution process. In this study, it was decided to keep the maximum value each four components. This process reduces the matrix from a size of 1000 x 16 to 250 x 16. The third layer consisted in generating linear combinations of the obtained matrix after pooling process. For the sake of computational efficiency, 250 x 16 matrix was previously transformed into a vector of 4000 components. The lineal combination of this number of components is performed 15 times, producing a vector of 15 components. This final vector represents the output data, with the same stratigraphy format that the data synthetically generated (i.e. values of shear-wave velocity for each 2 m-layer). Thus, the distribution of the dynamic properties is obtained down to a depth of 30 m.

The complete neuronal network comprised 60239 parameters that required calibration. For this purpose, 90 % of the generated database was utilized and the remaining 10 % for the evaluation of results. It is necessary to highlight that the neuronal network was built and calibrated using the free access library called Tensorflow [10].

5. Results

Fig. 4 reports five samples randomly chosen from the 10 % of the database used for the evaluation of the efficiency of the proposed system. The upper graphs present the dispersion curves, which are the input data of the neuronal network. The lower graphs present two distributions: the synthetic shear-wave velocity profiles shown in blue, from which the theoretical dispersion curves were calculated, and those in red estimated from the convolutional neuronal network developed. As it is observed, the level of similarity between the real (synthetic) and estimated profile is significant.

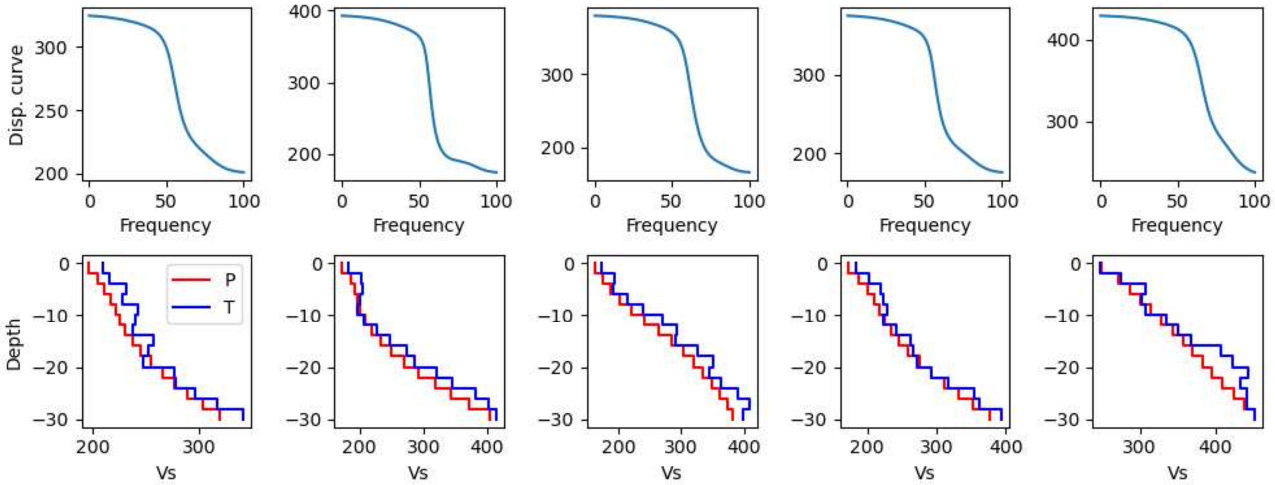

Fig. 4 – Comparison between the synthetic shear-wave velocity profiles and those evaluated by the proposed convolutional neuronal network

6. Discussion

This study represents a first attempt of generating an appropriate inversion model to be applied in obtaining accurate shear-wave velocity profiles based on the dispersion curve of phase velocities of Rayleigh waves mainly obtained by MASW tests in Lima, Peru. The main objective was to confirm that a neuronal network can adequately estimate the stiffness variation of a multilayered medium with a stable precision. The obtained results suggest that the application of this type of neuronal network is possible; however, it is necessary to perform significant improvements, which are:

Complexity of the neuronal network: Any reader familiar with machine learning topics can appreciate that, even though 60239 parameters were considered, this developed network can be still considered as small and simple when compared with those currently implemented. This can be considered as a good starting point, since it means that the level of precision has the potential to increase significantly. Nowadays, there are several configurations utilized in neuronal networks, so it is necessary to evaluate which is the most suitable for this type of research.

Improvement of the database: The strategy applied in the generation of the synthetic soil profiles does not represent all the possible configurations observed in reality. Thus, it is necessary to implement additional strategies to complement the generated database. In addition, it can be considered that 1000 shear-wave velocity profiles is a small number for the current standards.

Modifications in the input data: The implemented neuronal convolutional network uses as input data the dispersion curve which is calculated in the pre-processing of the recorded wavefield during MASW tests. As a possible variant, it can be considered the utilization of the raw data from this type of tests, which could increase the performance of the network since pre-processing the data can cause a loss in the information related to the experience of the person in charge when selecting the shots and processing the field data.

Data from real tests: Even though the strategy of acquiring training and evaluation data involves the generation of synthetic data, it is crucial to perform field surveys for different soil deposits with diverse geomorphological conditions in order to (i) confirm that the final product works well in real cases and (ii) use these tests as baseline for the further generation of more realistic synthetic profiles. To these complementary tests, it is necessary to implement algorithms of random transformation of the generated profiles, such as data augmentation and others, with the objective of generating adequate synthetic profiles.

7. Conclusions

The present study aimed to analyze the implementation of machine learning algorithms in geophysical inversion problems, in particular, the adequate estimation of shear-wave velocity profiles from dispersion curves of phase velocities of Rayleigh waves. The convolutional network implemented suggested good accuracy for the inverted profiles down to 30 m depth, which is the overall requirement for site classification in most of the seismic codes worldwide. Even though, further updates of the algorithm would require the inclusion of more parameters for the calibration, in the form of real shear-wave velocity profiles or synthetically generated based on real data.

8. Acknowledgments

This work was supported in part by the Concytec–World Bank research program "Improvement and Extension of the services of the National System of Science, Technology and Technological Innovation" 8682-PE through its executing unit Fondecyt [contract 038-2019].

9. References

[1] Moya L, Gonzales C, Diaz M, Adriano B, Mas E, Zavala C, Koshimura S, Yamazaki F (2021): Concytec-World Bank project: Machine learning and Earth observation technologies for disaster mitigation. *17th World Conference on Earthquake Engineering, 17WCEE,* Sendai, Japan.

[2] Park C B, Miller R D, Xia J (1999): Multichannel analysis of surface waves. *Geophysics*, **64**, 3, 800-808.

[3] Haskell N A (1953): The dispersion of surface waves on multilayered half-space, *Bulleting of the Seismological Society of America*, **64**, 1685-1696.

[4] American Society of Civil Engineers (2017): *Minimum Design Loads and Associated Criteria for Buildings and Other Structures ASCE/SEI 7-16*.

[5] Ministry of Housing, Construction and Sanitation (2018): *Seismic Resistant Technical Standard E.030.*

[6] Okada H, Suto K (2003): *The Microtremor Survey Method*. Society of Exploration Geophysicists.

[7] Takeuchi H, Saito M (1972): Seismic surface waves. *Methods in Computational Physics: Advances in Research and Applications*, **11**, 217-295.

[8] Goodfellow I, Bengio Y, Courville A (2016): Deep Learning. *The MIT Press.*

[9] Boureau Y, Ponce J, LeCun Y (2010): A theoretical analysis of feature pooling in vision algorithms. *Proceedings of the International Conference on Machine Learning.*

[10] Abadi, M et al. (2015): TensorFlow: Large-scale machine learning on heterogeneous systems. Software available from tensorflow.org.

