Contemporary Engineering Sciences, Vol. 9, 2016, no. 15, 735 - 741
HIKARI Ltd, www.m-hikari.com
http://dx.doi.org/10.12988/ces.2016.6685

RR-PSO: Fast and Robust Algorithm to Invert Rayleigh Waves Dispersion

Dharma Arung Laby, Sungkono and Bagus J. Santosa

Physics Department, Faculty of Mathematics and Natural Sciences
Institut Teknologi Sepuluh Nopember (ITS)
Jalan Arief Rahman Hakim, Surabaya 60111, Indonesia

Ayi S. Bahri

Geophysics Department, Faculty of Civil Engineering and Urban Planing
Institut Teknologi Sepuluh Nopember (ITS)
Jalan Arief Rahman Hakim, Surabaya 60111, Indonesia

Abstract

Shear-wave velocity (V_s) is commonly used in geophysical and environmental studies as one of important parameters to characterize near surface study. This parameter can be estimated via the inversion of Rayleigh waves dispersion curves. In this paper, regressive-regressive particle swarm optimization (RR-PSO) algorithm has been developed and used to invert Rayleigh waves dispersion. The algorithm was tested and applied for synthetics (a free-noise and a noise-added) and field data. The results show that RR-PSO is a fast inversion tool and robust toward noise which can precisely determine the lithology of survey field.

Keywords: Rayleigh waves, Uncertainty analysis, RR-PSO, Global optimization

1. Introduction

Recently, near-surface shear-wave velocity (V_s) become popular because it is widely used in geotechnical and environmental studies [1]. This parameter, can be estimated using Rayleigh waves dispersion analysis [2]. To obtain V_s profile or seismic stratigraphy, there are three main procedures, i.e.: data acquisition, dispersion curves reconstruction, and dispersion curves inversion [1]. Inversion is the key point to obtain seismic stratigraphy, so that researchers have developed many algorithms to invert Rayleigh waves dispersion.

PSO is one of popular algorithm that has been implemented in geophysical inversion[3], because the algorithm can be processed at a relatively fast processed, easily implemented, and also can be used to provide uncertainty model [4]. PSO have several versions with different characteristics, one of them is regressive-regressive PSO (RR-PSO)[4,5]. RR-PSO has the greatest convergence rate of all PSO versions and easy in parameter determination [5].

Thus, in this work we used RR-PSO to obtain seismic stratigraphy by inverting dispersion curves and also, we examined the stability and robustness of RR-PSO. To do this, first we inverted a synthetic data to determine V_s profile and examined the algorithm. Then in final step, we inverted a field data that acquired in LUSI (Lumpur Sidoarjo) embankment to determine the field lithology. In order to know the accuracy, we also compared the inversion result with the 2D resistivity imaging.

2. Rayleigh waves

Rayleigh waves propagate in the earth surface as result of the interference of *P* and *SV* waves (vertically polarized shear waves) with the surface. Thus, the waves induce motion of earth particle eliptically retrograde where the amplitude exponentially decrease with depth, and also dispersive only in vertically heterogeneous or layered media [2].

Many methods have been developed to calculate Rayleigh waves dispersion. Sungkono and Santosa [6] have used fast generalized of reflection/ transmission (FGRT) method to calculate Rayleigh waves dispersion which is addopted in this paper.

3. Inversion of Rayleigh waves dispersion via RR-PSO

Regressive-regressive particle swarm optimization (RR-PSO) is a novel member of PSO family which is derived from the damped mass-spring system using finite difference [5]. In other words, this algorithm is developed by backward finite difference scheme for velocity and acceleration in that system. Thus, the algorithm can be written as :

$$v(t+\Delta t) = \frac{v(t) + \phi_1 \Delta t\big(g(t) - x(t)\big) + \phi_2 \Delta t\big(l(t) - x(t)\big)}{1 + (1-\omega)\Delta t + \phi \Delta t^2}$$

$$x(t+\Delta t) = x(t) + v(t+\Delta t)\Delta t,\ t, \Delta t \,\epsilon\, \mathbb{R} \quad (1)$$

where (x) denotes vectors position, (v) denotes vector velocities, g denotes the global position on the whole swarm, ϕ_1, ϕ_2 are the random global and local acceleration constants, and ω is real constant called inertia weight. RR-PSO have the greatest convergence rate of all family members, good parameter sets and is fast to find the global minimum of objective function [5].

In inversion of Rayleigh waves dispersion, vector position contains thickness and velocity of subsurface, $x = [H_1, H_2, \dots, H_n, Vs_1, Vs_2, \dots, Vs_n]$, where H and V_s represent layer thickness and shear-wave velocity repectively, while n is the number of layers. To obtain optimum model, objective function that known as rms (root mean square) is needed. Essentially, the inversion result is not unique [1]. To accomodate this problem, uncertainty analysis in inversion is needed [7]. Model uncertainty can provide global optimization solution through posterior distribution model (PDM), especially Markov Chain Monte Carlo (MCMC) method and other methods. In order to provide it, MCMC depends on the type of likelihood which is used in the inversion process [1]. Thus, in this paper RR-PSO is designed to provide PDM.

4. Synthetic data inversion

In order to assess the stability and robustness of RR-PSO in the dispersion curves inversion, noise-free and noise-added data are tested to estimate model parameters (thickness and V_s) and their uncertainty. Therefore, RR-PSO uses 200 particles and 100 iterations to estimate thickness and V_s while, V_p and ρ are estimated using equation as in [8]. PDM of parameters (thickness and V_s) has provided using trade of error approach [4,7]. Model uncertainty is represented by interquartile of PDM while optimum model represented by median of PDM. To know the robustness of RR-PSO, similarity index (SI) was used [8].

4.1 Noise-free data

The dispersion curves inversion using RR-PSO is implemented on noise-free synthetic data first. This algorithm can invert the dispersion curves properly as shown in Fig.1. The figure shows that true model and inverted model are very similar with SI value up to 96.07%. In the fitting curves, calculated data are identical with the observed data but the true and the inverted model are not. It shows that inversion of dispersion curve has a non-uniqueness solution. Fig.1c shows a very fast initial convergence during the first 20 iteration and then gradually converged close to zero.

1.2 Noise-added data

RR-PSO algorithm is also tested on noise-added data to examine and evaluate the RR-PSO performance on data noise. The inversion result illustrated in Fig.2 shows that RR-PSO is very robust and stable on noise-added data. The SI value is 96.03% and each model parameters have a small error. Fig. 1c and Fig. 2c demonstrate that noise presence in the data can shift the global minimum. It means that noise in dispersion curve can degrade the accuracy of inversion result. Meanwhile, the accuracy of each parameters generated by Rayleigh waves dispersion is decreasing with depth because the waves amplitude exponentially decrease with depth [2]. Thus, this method is good for imaging near-surface parameters. Fig. 1a and Fig. 1b show standard deviation of PDM that is used for the uncertainty estimation. As shown in the figures, the uncertainty is increased because of noise presence.

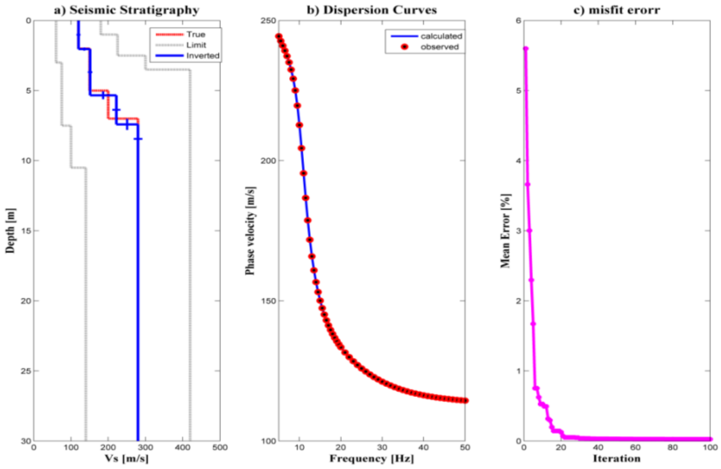

Fig.1 Inversion result of noise-free data. (a) Seismic startigraphy or V_s profile; (b) Fitting between observed data and calculated data; (c) misfit error as an iteration function

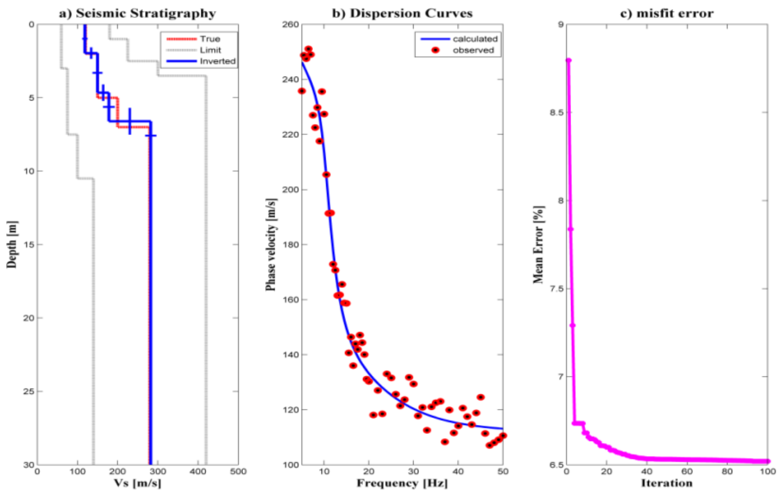

Fig.2 Inversion result of noise-contaminated data. (a) Seismic startigraphy or V_s profile; (b) Fitting between observed data and calculated data; (c) misfit error as an iteration function

5. Field data inversion

In the last section, we have implemented RR-PSO inversion for field data that is acquired in P.79 – P.82 LUSI (Lumpur Sidoarjo) embankment. LUSI area is composed of soft rocks which have high ductility while embankment material contains hard rock which have low ductility [9]. In this inversion, four layers model with Poisson's ratio 0.4-0.45 (for clay and sand) of each layer and large search space range is used to obtain seismic field stratigraphy. Fig.3 shows the result of field data inversion is characterized by four layers with a hard layer sandwiched between two soft layers. In order to validate the inversion result, the result is correlated with resistivity cross section in P.79–P.82 LUSI embankment [10]. Fig.4 shows the embankment generally has relative high value of resistivity above 11 m which is correlated as the interface between first and second layers in shear wave velocity (Fig.3) because embankment is harder than the layer below [9]. Furthermore, low resistivity in embankment is interpreted by fracture containing mud fluid [9]. Fig. 3 shows that the LUSI embankment consists of two layers, where the bottom is harder than the top. It is due to difference compaction factor in embankment layer, where the bottom suffered pressure from the top and the top is not. Thus, the bottom become more compact with higher V_s value. Based on Fig.3 and Fig.4, the layer bottom embankment consist of two layers, which may be clay and sand respectively. In this site, sand has higher resistivity and shear wave velocity than clay.

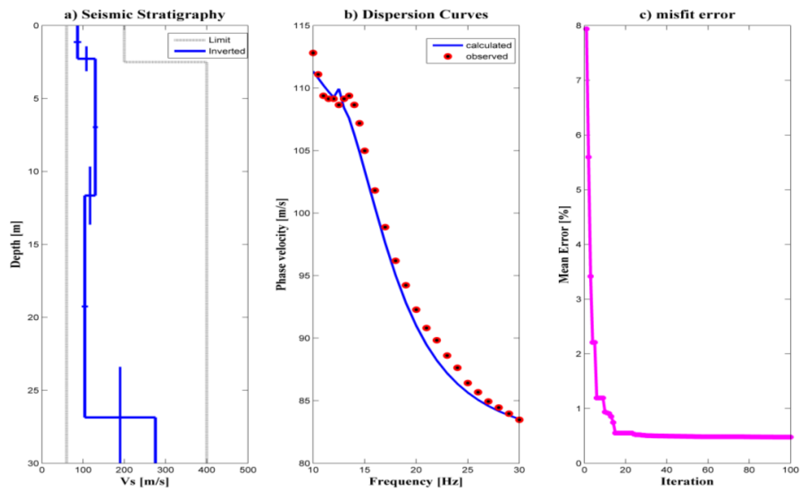

Fig.3 The inversion result of field data

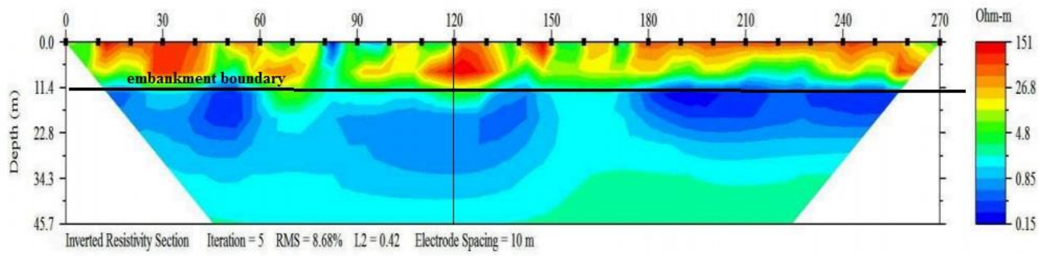

Fig.4 2D Resistivity imaging in P.79 – P.82 LUSI (Lumpur Sidoarjo) embankment [10]

6. Conclusion

RR-PSO algorithm is implemented to invert dispersion curves and examined the stability and robustness. This algorithm is stable, robust toward noise, and have a undergo rapid convergence in few iterations. Thus, it can obtain the subsurface parameters accurately. RR-PSO algorithm that has implemented in LUSI field data shows that the inversion result can well interpret the field lithology and help to assess stability LUSI embankment.

Acknowledgements. This work was supported by a grant which is provided by the Institute of Research and Public Services, Institut Teknologi Sepuluh Nopember, Indonesia for A.S.B. and B.J.S.

References

[1] Sungkono and B. J. Santosa, Differential evolution adaptive metropolis sampling method to provide model uncertainty and model selection criteria to determine optimal model for Rayleigh wave dispersion, *Arab. J. Geosciences*, **8** (2014), 7003-7023. http://dx.doi.org/10.1007/s12517-014-1726-y

[2] G. Dal Moro, *Surface Wave Analysis for Near Surface Applications*, vol. 1, Elsevier Inc., 2014.

[3] J. L. Fernández-Martínez, T. Mukerji, E. García-Gonzalo and Z. Fernández-Muñiz, Uncertainty assessment for inverse problems in high dimensional spaces using particle swarm optimization and model reduction techniques, *Math. Comput. Model*, **54** (2011), no. 11–12, 2889-2899. http://dx.doi.org/10.1016/j.mcm.2011.07.009

[4] J. L. F. Martínez, E. G. Gonzalo, Z. F. Muñiz, G. Mariethoz and T. Mukerji, Posterior Sampling Using Particle Swarm Optimizers and Model Reduction

Techniques, *Int. J. Appl. Evol. Comput.*, **1** (2010), no. 3, 27-48. http://dx.doi.org/10.4018/jaec.2010070102

[5] J. L. Fernández-Martínez and E. García-Gonzalo, Stochastic stability and numerical analysis of two novel algorithms of the PSO family: PP-GPSO and RR-GPSO, *Int. J. Artif. Intell. Tools*, **21** (2012), no. 03, 1240011. http://dx.doi.org/10.1142/s0218213012400118

[6] Sungkono and B. Santosa, Determine of Rayleigh wave dispersion using FGRT method, *Proceeding Int. Conf. Math. Sci. ICOMSc 2011*, (2011).

[7] J. L. F. Martínez, M. Z. F. Muñiz and M. J. Tompkins, On the topography of the cost functional in linear and nonlinear inverse problems, *Geophysics*, **77** (2012), no. 1, W1–W15. http://dx.doi.org/10.1190/geo2011-0341.1

[8] G. Dal Moro, VS and VP vertical profiling via joint inversion of Rayleigh waves and refraction travel times by means of bi-objective evolutionary algorithm, *J. Appl. Geophys.*, **66** (2008), no. 1-2, 15-24. http://dx.doi.org/10.1016/j.jappgeo.2008.08.002

[9] Sungkono, A. Husein, H. Prasetyo, A. S. Bahri, F. A. Monteiro Santos and B. J. Santosa, The VLF-EM imaging of potential collapse on the LUSI embankment, *J. Appl. Geophysics*, **109** (2014), 218-232. http://dx.doi.org/10.1016/j.jappgeo.2014.08.004

[10] A. Husein, B. J. Santosa and A. S. Bahri, Seepage Monitoring of an Embankment Dam Using Resistivity Method: A Case Study of LUSI Mud Volcano P.79 - P.82 Embankment, *Appl. Mech. Mater.*, **771** (2015), 213-217. http://dx.doi.org/10.4028/www.scientific.net/amm.771.213

Received: November 15, 2015; Published: July 10, 2016