Soil Dynamics and Earthquake Engineering 75 (2015) 147–157

Contents lists available at ScienceDirect

Soil Dynamics and Earthquake Engineering

journal homepage: www.elsevier.com/locate/soildyn

Grey Wolf Optimizer for parameter estimation in surface waves

Xianhai Song*, Li Tang, Sutao Zhao, Xueqiang Zhang, Lei Li, Jianquan Huang, Wei Cai

Institute of Geophysics and Geomatics, Hubei Subsurface Multi-scale Imaging Key Laboratory, China University of Geosciences, 388 Lumo Road, Wuhan, Hubei 430074, China

ARTICLE INFO

Article history:
Received 22 December 2014
Received in revised form
22 March 2015
Accepted 8 April 2015
Available online 29 April 2015

Keywords:
Swarm intelligence
Grey Wolf Optimizer
Rayleigh waves
Surface waves
Dispersion curves

ABSTRACT

This research proposed a novel and powerful surface wave dispersion curve inversion scheme called Grey Wolf Optimizer (GWO) inspired by the particular leadership hierarchy and hunting behavior of grey wolves in nature. The proposed strategy is benchmarked on noise-free, noisy, and field data. For verification, the results of the GWO algorithm are compared to genetic algorithm (GA), the hybrid algorithm (PSOGSA)-the combination of Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA), and gradient-based algorithm. Results from both synthetic and real data demonstrate that GWO applied to surface wave analysis can show a good balance between exploration and exploitation that results in high local optima avoidance and a very fast convergence simultaneously. The great advantages of GWO are that the algorithm is simple, flexible, robust and easy to implement. Also there are fewer control parameters to tune.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

In recent years Rayleigh waves have captured the interest of a constantly increasing number of researchers from different disciplines for a wide range of applications [1–3]. They can be used to obtain near-surface S-wave velocity models [4], to map bedrock [5], to infer subsurface properties in viscoelastic media [6], to determine Q of near-surface materials [7,8], to assess soil liquefaction potential [9], to delineate a shallow fault zone [10], to characterize pavement structure [11,12], to characterize seismic site structure [13], and to perform a joint inversion with refractions [14,15], reflection travel times [16], Love waves [17] or attenuation curves [18]. In these significant applications, utilization of Rayleigh wave dispersive properties is often divided into three procedures: field data acquisition [19–22], reconstruction of dispersion curves [23], and inversion of phase velocities [24–28].

Once Rayleigh wave dispersion curve is properly identified, its inversion is the key point to obtain S-wave velocity profiles [29–31]. A variety of local optimization methods have been developed and widely used to interpret Rayleigh wave data [32–34]. However, inversion of Rayleigh waves is typically a highly nonlinear, multiparameter, and multimodal inversion problem. The objective function for surface wave inversion has massive local optima with the number increasing exponentially with dimension. Consequently, linearized inversion strategies are prone to being trapped by local minima, and their success depends heavily on the choice of the initial model and on the accuracy of partial derivatives. Thus, global optimization methods that can overcome this limitation are particularly attractive for surface wave analysis, such as genetic algorithms [35,36], simulating annealing [37–39], and Monte Carlo [40–42].

Nature has always been an inspiration source for scientists. Mirjalili et al. conceived the idea of mimicking the social leadership hierarchy and hunting behavior of grey wolves into optimization problems and called the resulting technique as Grey Wolf Optimizer (GWO) [43]. GWO, a newcomer among population-based swarm intelligence optimization algorithms, is characterized by several appealing advantages: simplicity, flexibility, derivation-free mechanism, and local optima avoidance. Also, it is easy to implement; and it has fewer control parameters to adjust, and it has a fast convergence characteristic.

First, GWO is fairly simple. It is inspired from the particular leadership hierarchy and hunting behavior of grey wolves in nature. The simplicity allows computer scientists to simulate natural concepts and develop the algorithm more effectively. Moreover, the simplicity assists other scientists to learn the algorithm quickly and apply it to their problems. Second, flexibility refers to the applicability of GWO to different problems without any special changes in the structure of the algorithm. GWO is readily applicable to different problems since it assumes problems as black boxes. Third, GWO has derivation-free mechanisms. In contrast to gradient-based optimization approaches, GWO optimizes problems stochastically. It can be effectively used for addressing problems for which objective functions are non-differentiable, stochastic, or even discontinuous. Finally, GWO has superior abilities to avoid local optima compared to conventional optimization techniques. This makes GWO highly suitable for

* Corresponding author. Tel.: +86 27 67883251; fax: +86 27 67883251.
E-mail address: songxianhaiwcy@sina.com (X. Song).

http://dx.doi.org/10.1016/j.soildyn.2015.04.004
0267-7261/© 2015 Elsevier Ltd. All rights reserved.

solving highly nonlinear, multivariable, multimodal function optimization problems.

Mirjalili et al. [43] have recently tested GWO on unimodal, multimodal, fixed-dimension multimodal, and composite functions to benchmark its performance in term of exploration, exploitation, local optima avoidance, and convergence. It has been shown that the GWO algorithm is able to provide very competitive results compared to other well-known meta-heuristics. The GWO algorithm has been successfully applied to three classical engineering design problems and real optical engineering [43]. Song et al. [44] have successfully applied GWO for solving combined economic emission dispatch problems. Emary et al. [45] have used GWO for feature subset selection. Mirjalili [46] has investigated the effectiveness of GWO in training multi-layer perceptions (MLP). Saremi et al. [47] proposed the use of evolutionary population dynamics (EPD) in the GWO algorithm to further enhance its performance. Mirjalili et al. [48] have compared GWO with Multi-Verse Optimizer (MVO). Results from both applications and investigations show that the GWO algorithm has the superior performance not only in terms of exploring the promising regions extensively but also in terms of exploiting the optimum.

Although there are a lot of population-based algorithms in the literature, the operators of algorithms are usually designed to accomplish two phases [48]: exploration versus exploitation. In the former phase, an algorithm should be equipped with mechanisms to explore the search space as extensively as possible. In fact, promising regions of the search space are identified in this phase. In the exploitation phase, however, there should be emphasizes on local search and convergence towards promising areas obtained in the exploration phase. Exploration and exploitation are two conflicting stages with no specific mathematical definition. The majority of population-based algorithms have been tuned adaptively to smoothly transit between exploration and exploitation. For instance, the inertia weight in PSO is mostly decreased linearly from 0.9 to 0.4 in order to emphasize exploitation as iterations increase. However, there is no mechanism for significant abrupt movements in the search space for PSO and this will likely result in the poor performance of PSO. Therefore, finding a good balance between exploration and exploitation when designing an algorithm is challenging. There is no clear rule for an algorithm to realize the most suitable time for transiting from exploration to exploitation due to both unknown shape of search spaces and stochastic nature of population-based algorithms. This is the reason why current multi-solution stochastic optimizers still prone to local optima stagnation. Parameter estimation in surface waves is considered as a challenging problem due to its high nonlinearity and to its multimodality. It has been proven that GWO shows a good balance between exploration and exploitation that results in high local optima avoidance and a very fast convergence simultaneously. Therefore, the high level of exploration and exploitation that may assist GWO to outperform other optimizers in this field motivates our attempts to investigate its efficiencies in parameter estimation in surface waves.

In this study, we demonstrate a GWO application on surface wave data for near-surface S-wave velocity profiles. The proposed procedure is tested on noise-free, noisy, and field data. Furthermore, the results of the GWO algorithm are compared to GA, PSOGSA, and local search algorithm to further verify the performance of GWO. Results from both synthetic and field data demonstrate that GWO has the high level of exploration and exploitation that result in high local optima avoidance and a very fast convergence simultaneously in parameter estimation in surface waves.

2. Grey Wolf Optimizer (GWO)

The social hierarchy and the hunting behavior of grey wolves are mathematically modeled by Mirjalili et al. [43] in order to design GWO.

2.1. Social hierarchy

Grey wolf belongs to Canidae family. Grey wolves are considered as apex predators, meaning that they are at the top of the food chain. Grey wolves mostly prefer to live in a pack. Of particular interest is that they have a strict social dominant hierarchy from alpha, beta, delta, to omega.

In order to mathematically model the social hierarchy of grey wolves when designing GWO, the fittest solution is considered as the alpha (α). Consequently, the second and third best solutions are named as the beta (β) and the delta (δ), respectively. The rest of the candidate solutions are assumed to be the omega (ω). In the GWO algorithm, the hunting (optimization) is guided by α, β, and δ. The ω wolves follow these three wolves.

2.2. Encircling prey

In addition to the social hierarchy of grey wolves described above, group hunting is another interesting social behavior of grey wolves. According to Muro et al. [50], the main phases of grey wolf hunting include: (1) Tracking, chasing, and approaching the prey; (2) Encircling, pursuing, and harassing the prey until it stops moving; (3) Attacking towards the prey. In order to mathematically model encircling behavior, the following equations are proposed [43]:

$$D = |C \cdot X_p(t) - X(t)| \tag{1}$$

$$X(t+1) = X_p(t) - A \cdot D \tag{2}$$

Where t indicates the current iteration; A and C are coefficient vectors; X_p is the position vector of the prey; and X indicates the position vector of a grey wolf. The coefficient vectors $A = a \cdot (2r_1 - 1)$ and $C = 2r_2$. where a is linearly decreased from 2 to 0 over the course of iterations;r_1,r_2 are random values in [0,1]; so A is random values in the interval $[-a, a]$.

2.3. Search for prey (exploration)

Grey wolves mostly search according to the position of the alpha, beta, and delta. They diverge from each other to search for prey and converge to attack prey. In order to mathematically model divergence, A is utilized with random values greater than 1 or less than -1 to oblige the search agent to diverge from the prey. This emphasizes exploration and allows GWO to search globally. That is, $|A| \geq 1$ forces the grey wolves to diverge from the prey to hopefully find a fitter prey.

Another component of GWO that favors exploration is C. The C vector contains random values in [0, 2]. This component provides random weights for prey in order to stochastically emphasize ($C \geq 1$) or deemphasize ($C < 1$) the effect of prey in defining the distance in Eq. (1). This assists GWO to show a more random behavior throughout optimization, favoring exploration and local optima avoidance. It is worth mentioning that C is not linearly decreased in contrast to A. GWO deliberately requires C to provide random values at all times to emphasize exploration/exploitation not only during initial iterations but also final iterations. This component is very helpful in case of local optima stagnation, especially in the final iterations.

2.4. Attacking prey (exploitation)

In order to mathematically model approaching the prey, the value of a is linearly decreased. Thus A is a random value in the interval $[-a, a]$. When random values of A are in [-1,1] ($|A| < 1$), GWO forces the wolves to attack towards the prey.

Download English Version:

https://daneshyari.com/en/article/303963

Download Persian Version:

https://daneshyari.com/article/303963

Daneshyari.com