6th International Conference on Earthquake Geotechnical Engineering

Search for High Cut Slope Sliding Surface in Earthquake Conditions based on GSS-PSO Algorithm

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ABSTRACT

Artificial high cut slopes have led to many problems such as exfoliation, erosion and collapse, seriously affecting the safety and normal operations of construction sites. Making protective measures on the most dangerous sliding surface not only can improve the stability of these slopes, but also can enhance economic benefit. The PSO algorithm has fast convergence, high search precision and wide applicability. Its introduction greatly improves the search efficiency for sliding surfaces. However, the standard PSO easily falls into a local optimal solution. This paper introduces particle swarm optimization based on genetic select strategy (GSS-PSO) in the search of high cut slope sliding surfaces, which enhances the global search ability by increasing the diversity of particles group and thus improves the search efficiency of sliding surfaces. With an engineering example, we verify that GSS-PSO has higher accuracy and adaptability than standard PSO algorithm in search of sliding surfaces.

Introduction

With the development of coal mining in China, artificial high cut slopes inevitably arise during open-pit coal mine excavation. The instability of high cut slopes, exfoliation, erosion and collapse, and their frequent occurrences seriously affect the safety and normal operations of construction sites. The stability problem of high cut slopes has attracted much scientific attention.

The analysis of high cut slope stability is necessary for common projects. There are a large number of analytical methods, among which the limit equilibrium slice method has been widely applied. In

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Funded by the National Natural Sciences Foundation of China (No.41302278 and No.41272306)

stability analysis, the limit equilibrium slice method assumes that sliding surfaces are all arc-shaped. The safety factor is defined as the ratio of the resistant shear force to the driving shear force along the sliding surface. According to the short board effect, it is the sliding surface which corresponds to the minimum safety factor that determines the stability of that region. A certain type of sliding surface is artificially assumed, with high degree of uncertainty. Therefore, for accuracy and stability, we need to search for all potential sliding surfaces and select the sliding surface with the minimum safety factor as the most dangerous sliding surface.

Particle swarm optimization (PSO) is a swarm intelligence-based evolutionary computing method. Through information sharing, particles move from disorder to order and finally obtain the global optimal solution. Through iterations, the particles follow their personal historical best positions and the group best position to update their positions and eventually find the global optimal position. PSO is an excellent intelligent optimization method with simple implementation, fast convergence and easy operation.

As for the existing soil slopes in our studying area, all the sliding surfaces are arc-shaped. At present, many methods such as the Monte-Carlo Method and particle swarm optimization algorithm have been used to the research for circular sliding surfaces. In PSO, particles take the center and the radius as their positions and converge to the most dangerous sliding surface through iterations.

Given the standard PSO algorithm's drawback that it easily converges into a local optimum, we improve the PSO algorithm on its global search capability for slope stability analysis, thereby further improve the accuracy of the slope stability analysis.

PSO and GSS-PSO Algorithm Optimal Solution Search Process

Optimal Solution Search Process of Standard Particle Swarm Algorithm

Particle swarm optimization (PSO) is an intelligent evolutionary computation technique, proposed by Dr. Eberhart and Dr. Kennedy in 1995. They designed particle swarm optimization and applied it to a variety of optimization problems and achieved remarkable results. After initialization, it updates the velocity (V) and position (x) of each particle according to equation (1) and (2).

$$V_{id}^{k+1} = \omega * V_{id}^{k} + c_1 * \mathrm{rand} * \left(p_{id} - x_{id}^{k}\right) + c_2 * \mathrm{rand} * \left(p_{gd} - x_{id}^{k}\right) \tag{1}$$

$$x_{id}^{k+1} = x_{id}^{k} + V_{id}^{k+1} \tag{2}$$

In equation (1) and (2):
i = 1, 2 ... m, where m is the number of particles;
d = 1, 2... n, where n is the dimension of the solution space;

V_{id}^{k} and x_{id}^{k} represent the d_{th} component of the i_{th} particle's velocity and position in the k_{th} iteration;
p_{id} is the d-dimensional component of the i_{th} particle's best position;

p_{gd} is the d-dimensional component of the best position in the entire group;

rand is a random number in [0, 1];
c_1 and c_2 are learning factors reflecting the degree that a particle follows its personal and the group's best position;
ω is the inertia weight, indicating the extent of the particles maintaining their speed.

Optimal Solution Search Process of Particle Swarm Algorithm Based on Genetic Select Strategy

In the standard PSO, the population refers to a set of potential solutions. In the process of iterative search, a global information exchange is conducted among all the particles. Through the information exchange, the particles can modify their positions to achieve the goal for common evolution of the whole population. However in the standard PSO, the convergence of particles reduces population diversity, making it easy to be trapped at a local optimal position. This paper introduces particle swarm optimization based on genetic select strategy (GSS-PSO) in the search of high cut slope sliding surfaces. GSS-PSO not only records optimal solutions, but also the worst global solution and the worst solution of each particle. Particles fly towards the position that gets them away from global worst position and their historical worst position, which increases the population diversity, thus improves the global search ability and greatly reduces the possibility of trapping in a local optimum.

In addition to (1) and (2), GSS-PSO also contains Velocity (V) and displacement (x) equations as below:

$$V'^{k+1}_{id} = \omega * V_{id}^{k} + c_1 * rand * \left(x_{id}^{k} - p_{idw}\right) + c_2 * rand * \left(x_{id}^{k} - p_{gdw}\right) \quad (3)$$

$$x'^{k+1}_{id} = x_{id}^{k} + V'^{k+1}_{id} \quad (4)$$

In equation (3) and (4):

p_{idw} is the worst personal position;

p_{gdw} is the global worst position.

Specific steps of the GSS-PSO algorithm are as follows:

1) Initialization: Calculate the fitness value of each particle according to fitness equation; Find the particle with the best fitness in the population as the global best particle and record its position and velocity; Find the particle with the worst fitness in the population as the global worst particle and record its position and velocity; Take current fitness as each particle's best personal fitness as well as worst personal fitness.
2) For each particle,
    a) Based on equation (1) and (2), generate a new particle p, and calculate its fitness;
    b) Based on equation (3) and (4), generate a new particle p', and calculate its fitness;
    c) Compare the fitness of particle p and p', and select the particle with high fitness to enter the offspring.
3) For each particle, update its history optimal position p_{id} if current fitness is better than its historical optimal fitness; Update the global optimal position p_{gd} if current fitness is better than global optimal fitness.
4) For each particle, update its history worst position p_{idw} if current fitness is worse than its history worst fitness; Update the global worst position p_{gdw} if current fitness is worse than global worst fitness.
5) Check conditions of stop strategy. If conditions are satisfied, then stop updating and end iteration; otherwise, skip to step 2.

The Implementation Process of GSS-PSO Searching for Critical Sliding Surface

Based on the basic principles of GSS-PSO, this paper takes the simplified Janbu Method as an example to illustrate the basic application of GSS-PSO in slope stability analysis.

Determine the Fitness Function

Combine the basic principles of the simplified Janbu Method and GSS-PSO: set slope stability coefficients as particle's fitness to evaluate its position. See equations b:

$$F_s=\frac{\sum_{i=1}^{n}[c_i b_i+(1-k_H)W_i \tan\varphi_i]\frac{1}{m_{\theta_i}}}{\sum_{i=1}^{n}[(1-k_v)W_i \sin\theta_i+k_v W_i \cos\theta_i]} \tag{5}$$

$$m_{\theta_i}=\cos\theta_i+\frac{\sin\theta_i \tan\varphi_i}{F_s} \tag{6}$$

In equation (5) and (6):
F_s is the slope stability coefficients;
c_i is the soil cohesion on slice i;
b_i is the width of slice i;
W_i is the gravity of slice i;
φ_i is the angle of internal friction on slice i;
θ_i is slice i sliding surfaces tangent to the center point and the angle horizontally;
k_H and k_v is seismic horizontal and vertical acceleration respectively.

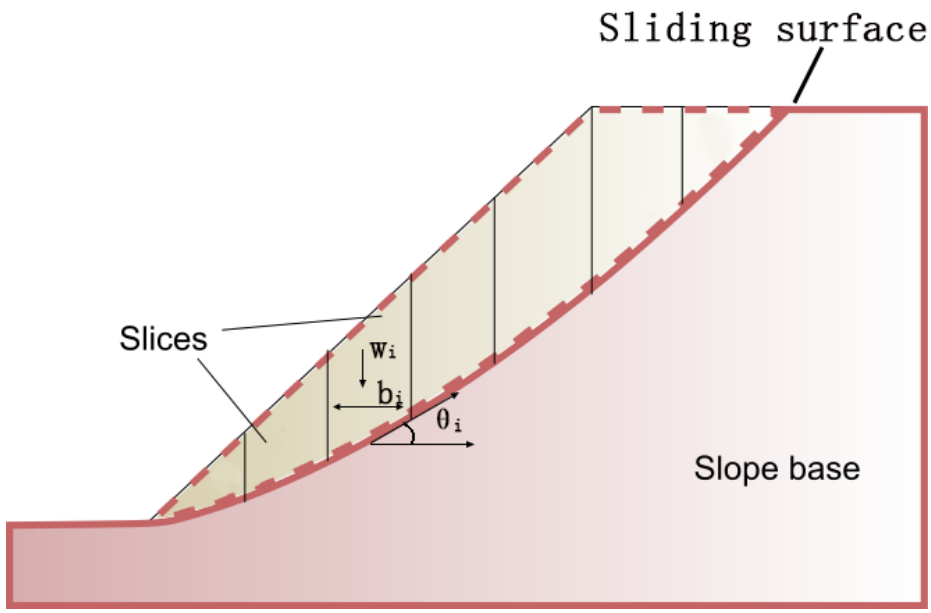

Figure 1. Division of the slope mass in the simplified Janbu Method.

Random Determine Initial Population

According to the GSS-PSO principle, the position vector is set to a 3D vector, which is composed of the horizontal and vertical coordinates and radius of the center. According to the principle of divisional search strategies, it randomly determines m center O_i in a certain range (x_i, y_i) and radius R_i, i=1,2,... , m.

Iteration

According to equation (1), (2), (3), (4), we constantly update the positions and velocities of all particles in the solution space, then obtain the stability coefficient based on the fitness function, until the stopping condition is met. Finally, we find the minimum safety factor.

Engineering Example

Hequ County is located in the northwestern area of Xinzhou City. Xinzhou Shanxi Coal Industry

Co. Ltd. Mitac Liangjia moraine open pit is located 15 km northeast to the county Crocodiles. The geographic coordinates are 111°15'34"-111°20'23" (east longitude) and 39°22'14"-39°24'54" (north latitude). The ore field measures about 4.88 km between its north and south end, and about 6.895 km between its west and east end. The area of the ore field is about 16.953km^2.

The most typical soil slope of Mitac Liangjia moraine open pit mining district stope slope is selected as an example. The goal of open pit stope slope stability evaluation is to design a stable slope with a certain mine height and slope angle, and make sure it have a reasonable and safe period of use and the most possible economic benefits. The slope is located at the east stope (see sectional view of the following Figure 4), and the overall slope angle is37°. The slope height is 150 meters (elevation from 980 meters to 1130 meters), with a total of 15 steps. From the lithological composition of the slope, the upper distribution is consisted of about 80 meters thick of Q_3 loess, over 20 meters thick of Q_2 loess and 30 meters thick of Tertiary red clay. The stratigraphic distribution from top to bottom is Q_3 loess, Q_2 loess and Tertiary red clay. The ore field seismic intensity is 6 degrees, with design of the basic earthquake acceleration at about 0.05g. According to the hydrological data, the region ground water level elevation is from 830 meters to 890 meters. It is lower than the slope foot by about 100 meters. So this paper does not consider the effect of the groundwater on the slope stability.

The sliding surface which needs to be searched majorly includes Q_3 part, Q_2 part, Tertiary red clay section and overall sliding surface. Therefore, the search for the interval from bottom to top in turn is divided into sections I, II, III, and overall, as shown in Figure 4. Each interval search diagram is shown below.

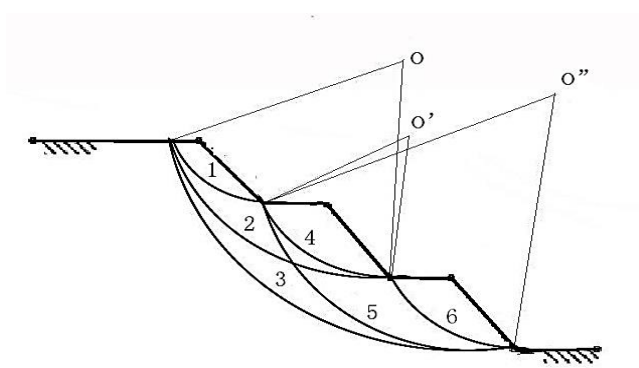

Figure 2. Search diagram of the interval

Assuming that the slope line is consisted of n nodes, there is a total number of $(n-1)(n-2)/2$ slippery arcs. Slope shown in Figure 2 has a total of 7 nodes, so there should be 15 slippery arcs. For clarity, only six typical slippery arcs and three typical slippery arcs' centers and radius are drawn. Using divisional search strategies, we can find out the most dangerous sliding surfaces and the potential sliding surfaces of the high cut slope. Because potential sliding surfaces are also

likely to exceed the safety factor, they may have to be protected in practical applications to ensure the slope stability.

Based on equation (5) and (6), we use the soil bulk density, cohesion, internal friction angle, and the slides parameters in different search surfaces to calculate the safety factors of different surfaces. Specific soil shear strength parameters are presented in Table 1.

Table 1. Mechanical calculation parameters reference value table

Soil sample name	bulk density(kg/m^3)	Cohesion(kPa)	internal friction angle(°)
Q_3 loess	1550	35	26
Q_2 loess	1890	50	29
Red clay	1770	120	31

We take the toe as the origin of coordinates, and respectively use standard PSO and GSS-PSO algorithms to search terms when this slope is in static and earthquake conditions. The flow chart is shown in Figure 3.

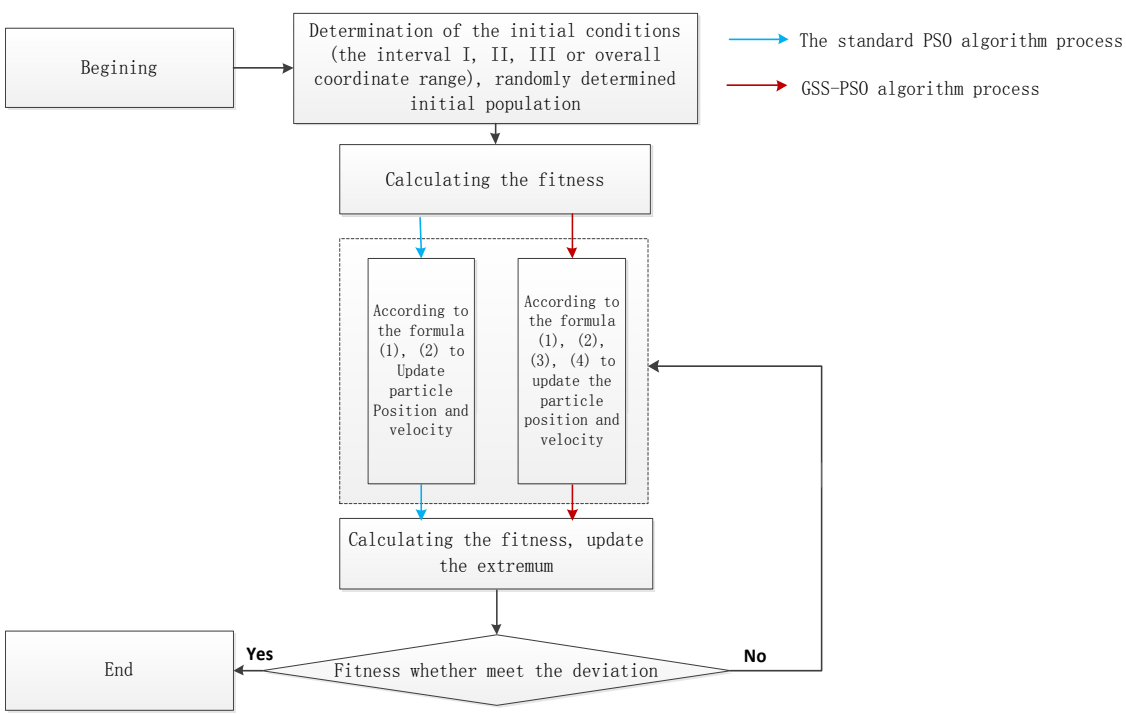

Figure 3. Flow chart for PSO and GSS-PSO algorithm

According to the different ranges, different initial conditions are set. Results of the two different methods are presented in Table 2.

Table 2. Comparison of calculation results for PSO and GSS-PSO methods

Potential sliding surface	Calculation Method	Safety factor in static conditions	Safety factor in earthquake conditions
Overall	PSO	2.33	1.75
	GSS-PSO	2.22	1.66
Q_3 loess step	PSO	1.08	1.10
	GSS-PSO	1.03	1.06
Q_2 loess step	PSO	2.15	1.62
	GSS-PSO	2.07	1.53
Red clay step	PSO	3.13	1.83
	GSS-PSO	2.96	1.64
Q_3+Q_2 loess	PSO	1.88	0.98
	GSS-PSO	1.75	0.86
Q_2 loess+red clay step	PSO	3.05	1.77
	GSS-PSO	2.83	1.70

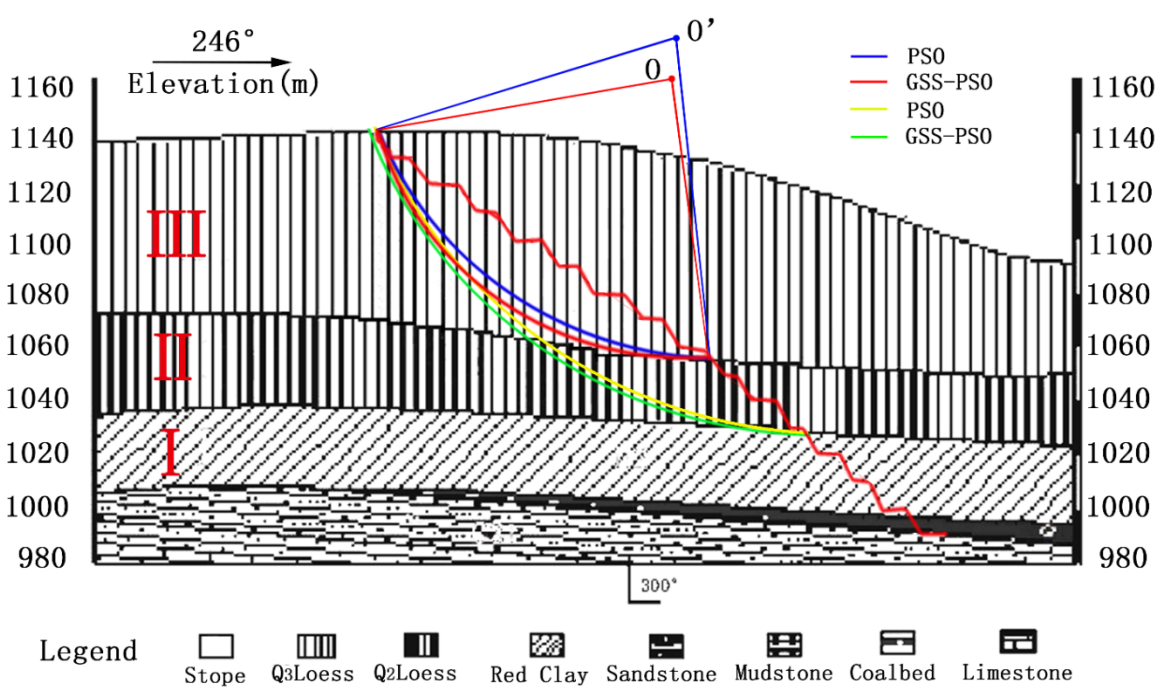

Figure 4. Comparison between results of PSO and GSS-PSO methods

According to Table 2, the most dangerous sliding surfaces are different in different conditions, especially in the interior Q_3 loess, showing that Q_3 loess is most easily damaged. Figure 4 shows that Q_3 loess is prone to sliding under static conditions. Q_3+Q_2 loess is prone to sliding under earthquake conditions. The most dangerous sliding surface under different conditions searched by these two methods are shown in Figure 4, indicating the differences between PSO and GSS-PSO in searching sliding surfaces. It is found that PSO falls into a local optimum while GSS-PSO can find a better solution. Under various conditions, safety factor of Q_3 loess step is close to 1.0, while Q_2 loess and red clay stairs are stable. In the meanwhile, Q_2 loess is vulnerable to be affected by vertical fractures of Q_3 loess until damage appears. Site survey also shows the existence of this case.

GSS-PSO algorithm uses obviously less time than the standard PSO algorithm, showing that GSS-PSO algorithm can find the optimal solution faster. As shown in Table 2, the minimum safety factor calculated by the standard PSO algorithm is larger than that calculated by the GSS-PSO, suggesting that the standard PSO algorithm is prone to fall into local optimum, which appears as a *premature* phenomenon. It is found that the global search capability of the GSS-PSO algorithm is obviously stronger than that of the standard PSO. The GSS-PSO algorithm can find a more optimal solution with relatively higher accuracy, and it can basically reach the global optimal solution in the partition search strategy.

Conclusions

In this paper, a method combining intelligent computing method and simplified Janbu Method is applied to the analysis for the most dangerous sliding surfaces of high cut slopes. This method is applied to an engineering practice and its validity is confirmed through experiments and calculations.

In solving practical problems, the standard PSO easily falls into a local optimization, failing to reach the global optimal solution. The standard PSO has low search accuracy and relies on the stability of the parameters. In view of these drawbacks of the standard PSO, this paper introduces particle swarm optimization based on genetic select strategy (GSS-PSO), which greatly improves the convergence rate, the independence to initial parameters and the search capability for a global optimal solution.

Using the safety factor calculated by simplified Janbu Method as the Fitness Function, GSS-PSO is applied to the search for sliding surfaces. Results suggest that the search accuracy of GSS-PSO is better than that of the standard PSO.

Acknowledgements

This research was funded by the National Natural Sciences Foundation of China (No.41302278),

(No.41272377) and (No. 41272306), and the Fundamental Research Founds for National University, China University of Geosciences (No. CUG120119). The authors would like to thank the reviewer for his detailed comments and valuable review.

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