Numerical-simulation-based Landslide Warning System and Its Application

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Abstract. Landslide early warning is a systematic project involving multidisciplinary integration, i.e. geology, mechanics, engineering, monitoring technology, and information technology. When conducting landslide studies, due to the limitation of failure theory of geological body, landslide warning system is purely based on monitoring data nowadays, so it is difficult to integrate interdisciplinary techniques. A trigger condition based prediction theory and disaster stage judgment approach are introduced, with which the landslide time prediction is converted to the disaster stage judgment. The definition and significance of fracture degree is presented, by which the disaster stage judgment is convert to inner fracture state analysis. At last, the numerical-simulation-based landslide warning system is discussed in detail. This system contains four parts, namely parameter acquisition part, disaster kernel analysis system, current state back analysis part, and landslide reliability evaluation part, respectively. In the first part, the essential parameters and its acquisition method is presented, and then the necessity and advantages of dimensional analysis is discussed. In the second part, the new numerical method named continuous discontinuous element method (CDEM) is introduced, and main features, i.e. Lagrange equation, strain strength distribution criteria, element crack strategy, and indented point & indented edge contact model is introduced. In third part, the inverse analysis method of current parameters of geological body based on monitoring data and numerical simulation is discussed. In the fourth part, the reliability evaluation steps are presented in detail. Finally, the sliding occurrence probability of Liangshuijing landslide in Chongqing, China is discussed, which demonstrated to show the precision and rationality of the proposed landslide warning system.

1. Introduction
Landslide is a kind of typical geological hazards. It is a movement process of the surface layer of mountains along the slope under gravity load, and it is induced by different natural or manual disturbance, i.e. rainfall, reservoir water fluctuation, earthquake, or manual excavation. To avoid or reduce casualties and property losses caused by the landslide disasters, effective and scientific landslide warning and prediction methods are needed.
Landslide disaster early warning is a system engineering, related to multi-disciplinary mixing, i.e. geology, mechanics, engineering and monitoring technology. Due to the limitation of failure theory of geological body, most landslide warning approaches are purely based on monitoring data nowadays, i.e. grey system model (Liao, 1996; Yang, et al, 2002), growth curve forecasting model (Li, et al, 1999), neural network methods (Neaupane, et al, 2004; Pradhan, et al, 2010), three stages model (Chen, 2000).
Predicting the potential landslide time based on trends of monitoring curve is the common feature of these models. However, the occurrence time of trigger conditions (i.e. rainfall) in future may not be determined totally, so the time prediction of landslide is not precise enough.

Numerical simulation plays a significant role in the stability analysis and prediction of landslide, and FEM and DEM are two main numerical methods. FEM is good at simulating elastic and plastic deformation of soil and rock slope under static or dynamic loads. Duncan (1996) discussed the state of art of FEM in landslide simulation, Quecedo, et al (2004) simulated a fast landslide using FEM, and Zheng, et al (2004) suggested a strength reduction FEM for soil and rock slope. DEM is expert in solving discontinuous problems, such as the damage, fragmentation and movement process of soil and rock slope. Zabuski, et al (2005) simulated the failure process of jointed rock slope using UDEC; Wu, et al (2011) modeled the characteristics of the Tsaoling landslide by DDA. Fan, et al (2013) studied the slope instability and failure with PFC, and Feng, et al (2014) discussed the influence factors of sliding distance of Jiweishan landslide based on CDEM.

In this paper, a landslide warning system framework based on numerical simulation and new failure theory is discussed in detail.

2. Trigger condition prediction and disaster stage judgment

Due to the uncertainty of occurrence time of trigger factors, it is difficult to warning or predicting the exact landslide time. A trigger-condition-based warning approach is suggested. In this method, time prediction is transformed into disaster stage judgment (Fig. 1), and four stages are divided for representing landslide state.

![Figure 1. Comparison between stage judgment and time prediction](image)

With the landslide evolution, geological body experiences five states, which are continuous media, fracture media, blocks, granular media and flow media (Fig. 2). With the evolution of geological body, the fractures will increase correspondingly, so fracture is a useful index for landslide stage judgment. Fracture degree is adopted to represent the state of the landslide. Fracture degree $D$ is an independent variable obtained by numerical method (Eq. 1). Where, $A_c$ is the failure area in current state and $A_d$ is the failure area in a given disaster state.

$$D = \frac{A_c}{A_d}$$

3. Composition of the numerical-simulation-based warning system

The system contains four parts, which are parameter acquisition and input part, disaster kernel analysis system, possible disasters and current state simulation part, and landslide reliability evaluation part.

3.1 Parameters acquisition and input

For modelling a landslide, the geometric parameters and material parameters are needed first. When all the parameters and conditions are ready, the dimension analysis should be taken and the dimensionless quantities will be formed. Take homogeneous slope for an example (Fig. 3). The relationship between fracture degree and all kinds of arguments is shown in Eq. 2, where $\rho$, $E$, $\mu$, $C$, $T$, $\phi$, and $\psi$ denote density, elastic modulus, Poisson ration, cohesion, tensile strength, inner friction angle and dilation angle, respectively. $g$ means the gravity acceleration, $h$ represents the slope height and $\theta$ is the slope angle.

$$D = f(\rho, E, \mu, C, T, \phi, \psi, g, h, \theta)$$

Choosing $\rho$, $g$ and $h$ as the fundamental quantities, the dimensionless relationship could be written as
In Eq. 3, ten arguments are reduced to seven dimensionless quantities, but generally speaking, only \( C/\rho gh \), \( T/\rho gh \), \( \phi \), \( \psi \) and \( \theta \) are main factors.

3.2 Disaster kernel analysis system

This kernel analysis system is based on a numerical method named CDEM (Li, et al, 2005; Wang, et al, 2005). In this system, Lagrange equation is used to formulate the deformation and movement media; strain strength distribution criteria is used to represent the damage process of geological body (Li, et al, 2013), element crack strategy is used to simulate the fracture propagation, and indented point & indented edge contact model is used to calculate the movement of discrete media (Feng, et al, 2014; Wang, et al, 2015).

(a) Lagrange equation

Lagrange equations are shown in Eq. 4-5. Where, \( u_i \) and \( v_i \) are generalized coordinates, \( L \) means energy in Lagrange system, \( Q_i \) is non-conservative forces, and \( A \) represents work done by non-conservative force or internal dissipative energy of system.

\[
\frac{d}{dt} \left( \frac{\partial L}{\partial v_i} \right) + \frac{\partial L}{\partial u_i} = Q_i
\]

\[
Q_i = \frac{\partial A}{\partial u_i}
\]

For the Lagrange system containing particles, rigid bodies, elastic solids and fluids, the energy functional can be expressed as \( L = L^p + L^r + L^s + L^f + L^{inter} \). Where \( L^p \), \( L^r \), \( L^s \), \( L^f \) and \( L^{inter} \) are energies related to particles, rigid bodies, solids, fluids, and interactive effects respectively. Based on Lagrange equation, different coordinate systems, media, and element types could use different generalized coordinates (independent variable), but with the same calculation scheme form. (Fig. 4)

(b) Strain strength distribution criteria

In order to quantify the damage (fracture in microscope) in representative volume element (RVE), strain strength distribution criteria is introduced. Typical constitutive equations for RVE are shown in Eq. 6-7. Where, \( \sigma_{p=1,3} \) and \( \varepsilon_{p=1,3} \) denote three components of principal stress and strain; \( e = e_i + e_j + 2\mu e/(1-2\mu) \) represents compression or tension strain in certain direction. \( \tau_{ij} \) and \( \gamma_{ij} \) mean three maximum shear stress and shear strain. \( \lambda \) and \( G \) are Lame constant and shear modulus, respectively. \( e = e_1 + e_2 + e_3 \) means bulk strain. \( \alpha \), \( \beta \), \( 1-\alpha \) and \( 1-\beta \) mean microscope tensile intact degree, shear intact degree, tensile fracture degree, and shear fracture degree of material. \( \alpha \beta \) and \( 1-\alpha \beta \) denote microscope combined intact degree and combined fracture degree.

\[
\sigma = \alpha \beta (2G\varepsilon + \lambda e) + \begin{cases} (1-\alpha \beta)(2G\varepsilon + \lambda e) & (e < 0) \\ 0 & (e \geq 0) \end{cases}
\]

\[
\tau_{ij} = \alpha \beta G\gamma_{ij} + \begin{cases} (1-\alpha \beta)G\gamma_{ij} & (\gamma_{ij} \leq [e_i + e_j + 2\mu e/(1-2\mu)]\tan \phi, e < 0) \\ (\gamma_{ij} \geq [e_i + e_j + 2\mu e/(1-2\mu)]\tan \phi, e < 0) \\ 0 & (e \geq 0) \end{cases}
\]

Typical constitutive curves for strain strength distribution criteria are shown in Fig.5-Fig.6. In these two
curves, elastic modulus is 10GPa, Poisson ratio 0.3, inner friction angle 40 degree, linear tensile and shear strain strength is 0.02%, and broken tensile and shear strain strength is 0.2%. From Fig.5, the affection of the parameters of Weibull distribution is obviously observed. When $\lambda$ keeps constant, with the increase of $k$, the peak tensile stress increases gradually, and the softening stage gradually becomes steep. From Fig.6, with the increase of compressive stress $\sigma_c$, the peak shear stress and sliding stress increases gradually.

Figure 5. Tensile stress-strain curve under Weibull distribution
Figure 6. Shear stress-strain curve under Weibull distribution

(c) Element crack strategy
To eliminate or relieve grid sensitivity in CDEM, element crack strategy is used. In this strategy, Mohr-Coulomb criterion with a tensile cutoff (Eq. 8-9) is used to judge the failure state. If Eq. 8 is satisfied, tensile failure will happen, the fracture direction is perpendicular to $\sigma_3$. If Eq.9 is satisfied, shear failure will happen, and the included angle between fracture direction and $\sigma_3$ is $(\pi/4+\phi/2)$.

$$\sigma_3 > T$$  \hspace{1cm} (8)

$$-\sigma_1 \geq -\sigma_3 \tan^2 (\frac{\pi}{4} + \frac{\phi}{2}) + 2C \tan (\frac{\pi}{4} + \frac{\phi}{2})$$  \hspace{1cm} (9)

The element will be split into two elements by element cutting algorithm. If cutting direction is the same as the fracture direction, the quality of new created elements may be poor sometimes. In order to increase the robustness of the program, the cutting direction is limited in two types, cracks along the element boundaries, and cracks from one vertex of the element to the center of the opposite edge (Fig. 7).

Figure 7. Cutting types
Figure 8. Uniaxial compression test

A uniaxial compression test is executed for demonstrating the rationality of the element crack method. The model size is 10cm $\times$ 10cm, with the cohesion 3MPa, tensile strength 3MPa, and inner friction angle 0 degree. For traditional block-DEM, only boundaries could be cracked, so the failure plane could only be along the element boundaries. By element crack strategy, the failure plane is very smooth (Fig. 8), and the numerical failure angle (45 degree) agrees well with the theoretical one.

(d) Indented point & indented edge contact model
For simulating the movement and accumulation process of landslide, the contact detection method is need. In this paper, indented point & indented edge contact model is used, indented point is derived from block vertex, and formed by indenting the block vertex into each face. The formation process of indented edge is the same as indented points. The indented points and indented edges in a hexahedral element are shown in Fig. 9, and the indented distance $d$ is 0.1%-1% of the distance from vertex to the face center.
Due to indented points and indented edges are on the face of each element, their characteristic areas are

\[ A_{SS} = A_{ss} / N_v \]  \hspace{1cm} (10)

\[ A_{SE} = A_{se,i} + A_{se,j} \]  \hspace{1cm} (11)

Where \( A_{SS} \) and \( A_{SE} \) are the area of indented points and indented edges, respectively. \( A_{ss} \) denotes the area of host face. \( N_v \) means the vertex number in host face. \( A_{se,i} \) and \( A_{se,j} \) mean the areas of indented point \( i \) and \( j \). Numerical results about the failure process of a typical high and steep landslide based on above mentioned model is shown in Fig.10, which reveals that the combined model could solve the contact problems precisely and efficiently.

3.3 Possible disasters and current state simulation

Based on above mentioned disaster kernel analysis system, possible catastrophic state could be obtained by traversing all geological parameters. A simple numerical test about sliding volume under different inner friction angle is shown in Fig.11, where red color denotes sliding body, and blue color means sliding bed. In Fig.11, strain strength distribution criteria are adopted for the slope, with the maximal shear strain strength is \( 2 \times 10^{-3} \) and minimal shear strain strength \( 2 \times 10^{-5} \). From Fig.11, with the increase of inner friction angle, the sliding volume decreases gradually, and the shear outlet moves towards slope gradually. Fig.12 shows the relationship between dimensionless sliding volume and friction coefficient, where \( V_s \) denotes sliding volume and \( V_0 \) means total volume of the numerical model. From Fig.12, with the increase of friction coefficient \( \tan \phi \), the dimensionless volume decreases gradually, but the decreasing speed becomes slower gradually.

On the other hand, different inner friction angle will lead to different fracture areas. Fig.13 shows the relationship between friction coefficient and dimensionless fracture area, where \( A_f \) denotes fracture area.
and $A_0$ means the total interface area. From Fig. 13, with the increase of friction coefficient, the dimensionless fracture area decreases linearly. Fracture feature (i.e. number, distribution, displacement) comparison is a useful way to adjust the input material parameters (Fig.14). If the surface fracture feature of a slope in numerical results coincide well with the field monitoring data, the material parameters agree well with the field ones.

In Fig.14, the surface fracture in numerical model is obtained by counting the broken interface appearing on the slope surface, while the surface fracture in field is gotten by measuring the length and width of each crack. According to the definition of fracture degree in Eq. 1, different fracture degree in different disaster (i.e. different sliding volume) could be obtained, and the current state of the landslide could be determined.

3.4 Landslide reliability evaluation

When analyze the stability of the slope, randomness of material properties should be taken into account. A lot of methods based on reliability theory to evaluate the slope stability, i.e. Monte Carlo method (Tamimi, et al, 1989), probability estimates calculated moments method (TAN, 2001), response surface method (SU, 2006), stochastic response surface method (LI, 2010), and neural network (BI, 2010). A slope disaster status evaluation method based on the fracture degree and its reliability is presented. A random sample of geotechnical parameters accord with the certain probability distribution is obtained by the Latin hypercube sampling (LHS) method. A large number of numerical cases with different parameters are executed by CDEM, and the fracture degree for each case is obtained. Based on the law of large number, the probability of the status that reaches and exceeds the catastrophic status can be obtained. For executing landslide reliability evaluation, some steps should be followed.

(a) Based on the geometry parameters and boundary condition, set up the numerical model, and traverses all geological parameters to obtain different fracture area in different sliding volume. (b) Create parameter samples by means of Latin hypercube sampling method (LHSM). (c) Use stratified sampling method to form a group of random variables, then use numerical system to obtain the fracture area under different variables, and finally calculate fracture degree based on a given disaster (i.e. a given sliding volume). (d) Get occurrence probability of landslide with a given sliding volume under current parameters. The probability can be replaced by frequency when $N$ is large enough according to law of large numbers. If there are $M$ samples' fracture degree are larger than $D_p$ in $N$ samples, the probability of occurrence probability under the current parameters can be expressed as

$$P_r = P[D \geq D_p] = M / N$$  \hspace{1cm} (12)

4. Application

The generalized numerical model of Liangshuijing landslide in Chongqing, China is set up to execute the reliability evaluation (Fig. 15). The height of the slope is 256 m, the length is 673 m, the angle of slope is 24.0 degree, and the material parameters are shown in Table 1. The cohesion, tension strength, internal friction angle are assumed to be normal distribution. In this example, if the sliding body is the total accumulated layer, the dimensionless volume is 0.284 (here named such disaster as disaster DA). The sides and bottom conditions are normal restraint.

10,000 group random parameter samples were created by LHSM to ensure convergence. The probability density histogram of cohesion (tension strength) and internal friction angle are showed in Fig.16. The kurtosis coefficient and skewness coefficient of the parameter samples can be obtained by means of statistical analysis and the results show those values are far less than one. So, the parameter samples are
in accordance with normal distribution characteristics.

| Cohesion/10^4 Pa | Internal friction angle/° |
|------------------|--------------------------|
| 3.0x10^4         | 0                        |
| 6.0x10^4         | 10                       |
| 9.0x10^4         | 20                       |
| 1.2x10^5         | 30                       |
| 1.5x10^5         | 40                       |
| 1.8x10^5         | 50                       |

Figure 16. The probability density histogram of parameters of the samples

When all the samples are calculated by the numerical system, the different fracture degree based on disaster DA could be obtained. The relationship between fracture degree and parameters are shown in Fig. 17. From this figure, with the increase of internal friction angle and cohesion, the fracture degree decreases gradually. The relationship between occurrence probability of disaster DA and simulation times is shown in Fig.18. In figure 18, the occurrence probability has converged when the simulation times exceed 2000 times and the occurrence probability is 60.7%.

Figure 17. Relationship between fracture degree and parameters

Figure 18. Occurrence probability of disaster DA VS simulation times

5. Conclusion

Traditional landslide warning methods are based on time prediction. Due to the uncertainty of trigger condition, the prediction results will not be precise enough. A trigger-condition-based disaster stage prediction approach is proposed in this paper, by which the time prediction could be changed to disaster stage judgment. According to the relationship between disaster stage and fracture degree, the disaster stage judgment could be converted to fracture degree calculation, and the fracture degree could be obtained by numerical simulation.

A numerical-simulation-based warning system is introduced, which contains four parts, with the name parameter acquisition and input part, disaster kernel analysis system, possible disasters and current state simulation part, and landslide reliability evaluation part, respectively. Based on this numerical warning system, the potential landslide disasters could be predicted precisely and efficiently. The generalized numerical model of Liangshuijing landslide in Chongqing, China is set up to execute the reliability evaluation. The relationship between fracture degree and the probability distribution of cohesion and inner friction angle is discussed, and the probability of integral sliding with given parameters is obtained. Numerical results show that, based on the suggested parameters in this paper, the occurrence probability of disaster DA is 60.7%.

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