Development of Random Smoothed Particle Hydrodynamics Method for Landslide Risk Assessment

Zhengwen Qin[1], Yu Wang[2], Xin Liu[3,4], and Liang Li[5]

[1]Department of Architecture and Civil Engineering, City University of Hong Kong, Tat Chee Avenue, Kowloon, Hong Kong E-mail: zhengwqin2-c@my.cityu.edu.hk
[2]Department of Architecture and Civil Engineering, City University of Hong Kong, Tat Chee Avenue, Kowloon, Hong Kong E-mail: yuwang@cityu.edu.hk
[3]State Key Laboratory of Water Resources and Hydropower Engineering Science, Wuhan University, 8 Donghu South Road, Wuhan, China E-mail: xliu268-c@my.cityu.edu.hk
[4]Department of Architecture and Civil Engineering, City University of Hong Kong, Tat Chee Avenue, Kowloon, Hong Kong E-mail: xliu268-c@my.cityu.edu.hk
[5]School of Civil Engineering, Qingdao University of Technology, Qingdao, China E-mail: cellldl@126.com

Abstract: Landslide risk is often quantified as a product of landslide occurrence (or failure) probability and landslide consequence such as the landslide runout distance and volume of sliding mass. Many efforts have been made to estimate failure probability, but few studies focus on the estimation of landslide consequence, especially the landslide runout distance. This is probably due to the difficulty of slope stability analysis methods in simulating the whole process of a landslide (e.g., initiation of landslide, transportation and final deposition of the sliding mass). For example, without considering stress-strain relationship of soils, the factor of safety and critical slip surface obtained from limit equilibrium methods only correspond to initiation of landslide; while finite element/difference methods may suffer from grid distortion problems when simulating large soil deformation during transportation and final deposition of sliding mass during landslide. To properly assess landslide risk, a Monte Carlo simulation (MCS) based method called random smoothed particle hydrodynamics (RSPH) is proposed. In RSPH, random field theory is combined with a particle-based mesh-free numerical method called smoothed particle hydrodynamics (SPH), which can handle complex geometries and large deformation problems. The proposed approach is able to simulate the whole process of a landslide and provide reasonable estimations of both the failure probability and landslide consequence, leading to proper quantification of landslide risk.

Keywords: Monte Carlo simulation; random field; large deformation.

1 Introduction

Landslide is a common and severe geo-hazard which may cause severe casualties and significant economic losses. For example, a catastrophic landslide occurred near Po Shan Road in Hong Kong in 1972, which is with a sliding mass volume of about 38,000 m^3. It killed 67 people and destroyed two high-rise residential buildings (e.g., Yang et al. 2008). In 2006, a disastrous landslide occurred in Philippines, which has a horizontal runout distance of 3800 m and a sliding mass volume of 15 million m^3. A village located in the landslide runout path was destroyed completely, resulting in a loss of over 1100 lives (e.g., Evans et al. 2007). The casualties and economic losses induced by a landslide are often determined by the landslide runout distance and sliding mass volume. As illustrated in Figure 1, the runout distance is defined as the horizontal distance between the slope toe before landslide and the distal toe at the foot of the displaced soil mass after landslide. The sliding mass volume, illustrated by the shadow area in Figure 1, is defined as the volume of geo-materials that are sliding during the landslide process.

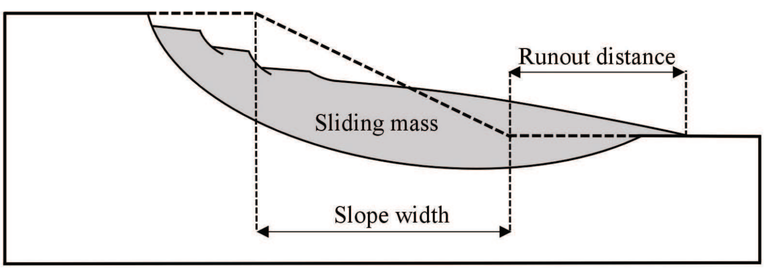

Figure 1. Illustration of landslide runout distance and sliding mass.

Proceedings of the 7th International Symposium on Geotechnical Safety and Risk (ISGSR)
Editors: Jianye Ching, Dian-Qing Li and Jie Zhang

Published by Research Publishing, Singapore.
ISBN: 978-981-11-2725-0; doi:10.3850/978-981-11-2725-0_IS8-6-cd

Landslide risk is often quantified as a product of landslide occurrence (or failure) probability and landslide consequence.In recent years, many probabilistic studies have been conducted to assess landslide risk. For example, random field theory is integrated with limit equilibrium (e.g., Wang et al. 2011) method or finite element method (e.g., Griffiths and Fenton 2004) to quantify landslide risk. However, most previous studies focus on the quantification of landslide occurrence probability, while the estimation of the landslide consequence, particularly the landslide runout distance, has rarely been studied, except a few examples on the sliding mass volume (e.g., Huang et al. 2013). This may be due to the difficulty in simulating the whole process of a landslide (e.g., initiation of the landslide, transportation and final deposition of the sliding mass). For example, the critical slip surface and factor of safety determined by the limit equilibrium method only correspond to the initiation of the landslide; while finite element/difference methods may suffer from mesh distortion problems when simulating large soil deformation problems which occurs during transportation and final deposition of the sliding mass. Because landslide runout distance and sliding mass volume are determined by the transportation and final deposition of the sliding mass, simulation of the whole process of a landslide is required, especially the large soil deformation that occurs after the landslide is initiated.

In order to properly assess the landslide risk including both the failure probability and landslide consequence, a Monte Carlo simulation (MCS) based method is proposed in this paper, called random smoothed particle hydrodynamics (RSPH), in which random field theory (e.g., Vanmarcke 1977) is combined with a particle-based mesh-free numerical method, called smoothed particle hydrodynamics (SPH). SPH is able to handle complex geometries and simulate large soil deformation problems. Therefore, the proposed approach can simulate the whole process of a landslide and well estimate the landslide occurrence probability, runout distance and sliding mass volume simultaneously, leading to proper quantification of landslide risk. Following this introduction, the framework of RSPH is firstly proposed. For illustration, the proposed method is then applied to quantify the landslide risk of a slope. The simulation results of a typical failed slope sample from MCS is demonstrated. Based on the MCS results, statistical analyses of the landslide runout distance and the sliding mass volume are performed.

2 Random Smoothed Particle Hydrodynamics (RSPH)

The proposed RSPH method combines random field theory with SPH in a Monte Carlo framework. RSPH has three key components: deterministic SPH model for landslide simulation, uncertainty modeling using random field theory and uncertainty propagation through Monte Carlo simulation. These components will be briefly described below.

SPH was originally developed to study astrophysics problems (e.g., Lucy 1977) and then applied to fluid mechanics (e.g., Liu and Liu 2003) and soil mechanics (e.g., Bui et al. 2008, 2011; Li et al. 2019). In SPH, the problem domain is discretized and represented by a number of individual particles which carry material properties (e.g., density, friction angle and cohesion) and state variables (e.g., displacement, velocity, stress and strain). The state variables of each particle can be calculated through an interpolation process over its neighboring particles within a certain area. Through interpolation process, the governing equations and constitutive equations become a set of ordinary differential equations which are only with respect to time. These equations can be further solved using time integration scheme, after which the time history of all state variables for all SPH particles can be obtained. SPH has advantages of handling complex geometries and simulating large deformation problems in geotechnical engineering. Therefore, it is can simulate the whole process of a landslide.

Soils are natural geo-materials affected by various geological process such as transportation, weathering and erosion of parent materials, therefore soil properties such as cohesion vary spatially and exhibit inherent spatial variability. Such uncertainty can be quantitatively modeled using random field theory, in which a soil property at different locations is represented by a random variable and the correlation among random variables at different locations is modeled through a correlation function, such as single exponential correlation function.

In order to propagate uncertainties from inherent spatial variability in soil properties through deterministic SPH model, Monte Carlo simulation (MCS) is employed in RSPH framework. MCS is a numerical process of repeatedly calculating a mathematical or empirical operator in which the variables within the operator are random or contain uncertainty with prescribed probability distributions (e.g., Ang and Tang 2007). In RSPH, SPH analysis is the mathematical operator and repeated many times, generating a great number of outputs for subsequent analysis. Due to its conceptual simplicity and robustness, MCS has been widely adopted in the reliability analyses of geotechnical problems such as slope stability (e.g., Wang et al. 2011), foundations (e.g., Wang 2011) and retaining wall (e.g., Low et al. 2011).

3 Illustrative Example

In this section, the proposed RSPH method is illustrated through a slope example. Figure 2 shows the slope geometry: a slope height H =10 m and a slope inclination angle of 26.6° to the horizontal (1:2 slope). The spatial variability of cohesion c' and tangent of friction angle tan ϕ' are modeled by a lognormal random field with a single exponential correlation function. The random field parameters (e.g., mean μ, standard deviation σ, and coefficient of variation COV = σ / μ) are summarized in Table 1. A single exponential correlation function in a two-dimensional space can be expressed as follows

$$R(\tau) = \exp\left(-2\frac{\tau}{\theta}\right) \tag{1}$$

where $R(\tau)$ is the correlation coefficient between soil properties at two different locations in a random field separated by an absolute distance τ . θ is the spatial correlation length which describes the distance within which the spatially random values tend to be correlated in a random field. For simplicity, the spatial correlation length in the vertical and horizontal directions are taken as equal (i.e., isotropic random field) in this illustrative example.

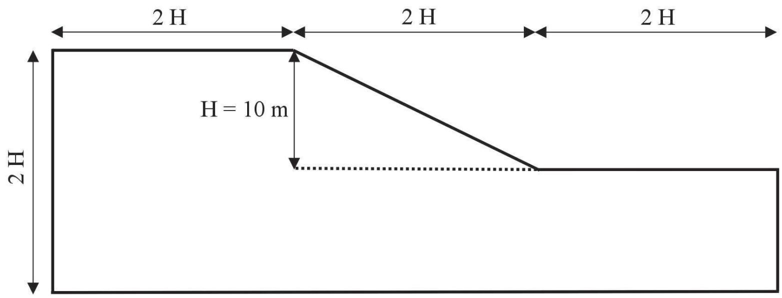

Figure 2. Slope geometry of the illustrative example.

Table 1. Summary of random field parameters used in the illustrative example.

Soil properties	Mean, μ	Standard deviation, σ	Coefficient of variation, COV	Isotropic spatial correlation length, θ (m)	Probability distribution
Cohesion, c' (kPa)	18.5	9.25	0.5	5	Lognormal
Tangent of friction angle, tan ϕ'	0.27	0.135	0.5	5	Lognormal

In SPH model, the Drucker-Prager constitutive model with non-associated flow rule is implemented to describe the elasto-plastic soil behaviour. Full-fixity boundary condition is applied to the horizontal base, where three layers of fixed boundary particles are generated outside the problem domain and share the same properties as the neighboring real particles (e.g., Bui et al. 2008). Free-roller boundary condition is applied to the left and right vertical boundaries, where ghost particles are generated as a mirror image of the real particles inside the problem domain. The Verlet time integration scheme is adopted to integrate the state variables of SPH particles including velocity, density, stress tensor and position. Gravity is firstly applied to all SPH particles to obtain the initial stress condition. The slope is modeled by totally 22450 SPH particles with a radius of 0.1 m.

To ensure a desired level of accuracy in the failure probability, the number of MCS samples should be at least 10 times greater than the reciprocal of the probability level of interest (e.g., Wang 2011). For a target failure probability of 0.1%, the number of MCS samples should be greater than 10,000. Therefore, the MCS sample size is chosen to be 10,000 in this study, which is sufficient to provide reliable probabilistic analysis results. Many random field simulators have been developed to generate spatially varying random field samples, such as local average subdivision method, Karhunen-Loève expansion and circulant embedding method. Because a large number of SPH particles and MCS samples is required in this study, the random fields samples are generated by circulant embedding method due to its high computational efficiency.

4 A Typical Failed Slope Sample from MCS

The random field samples of cohesion and friction angle of soils for a typical failed slope sample from MCS are illustrated in Figures 3 (A) and (B), respectively. Relatively weak soils represented by dark color are mostly located near the slope surface. The whole process of slope failure or development of landslide at different stages is shown in Figure 4. Dark color represents soils with relatively small displacement, and light color represents soils with relatively large displacement. Figure 4 (A) illustrates the initial slope geometry at t = 0 second, before landslide is initiated. Deformed slope geometry at t = 1 second is shown in Figure 4 (B). The slope may be divided into two zones, one with light blue for relatively large soil displacement and the other with dark blue for relatively small soil displacement. A slip surface can be identified as the boundary between these two different color zones. The soils with relatively large displacement represented by the light blue zone slide downward along the slip surface. At this stage, the maximum soil displacement is 0.45 m. Deformed slope geometry at t = 3 second is shown in Figure 4 (C). Sliding soils further move along the slip surface and spread onto the ground at the toe level of the slope with maximum soil displacement of 2.81 m. Figure 4 (D) shows the deformed slope geometry at t = 6 second, which is the steady state or final stage of the SPH simulation. Sliding soil mass deposit on the ground at the toe level of slope with runout distance estimated as 3.45 m. A SPH particle is considered sliding when its displacement is greater than a threshold value d_{st} (e.g., d_{st} = 0.1 m), based on which the location of the slip surface can also be determined, which is shown by a red line. The volume of sliding mass is the soil volume above the slip surface during the landslide, which is estimated as 131.4 m^3 in Figure 4 (D).

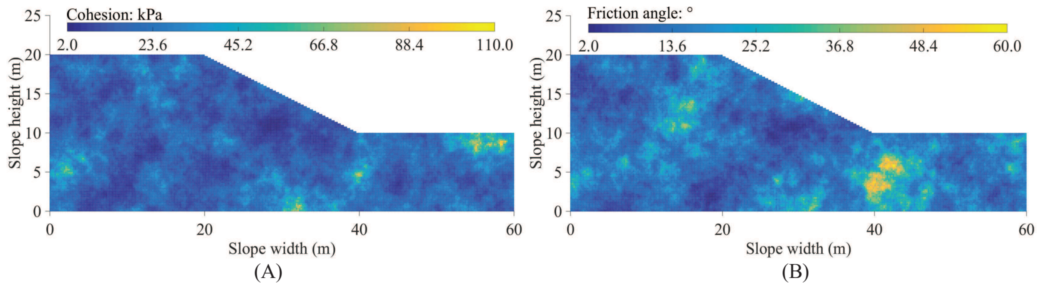

Figure 3. Random field samples of (A) cohesion and (B) friction angle of soils for a typical failed slope sample from RSPH

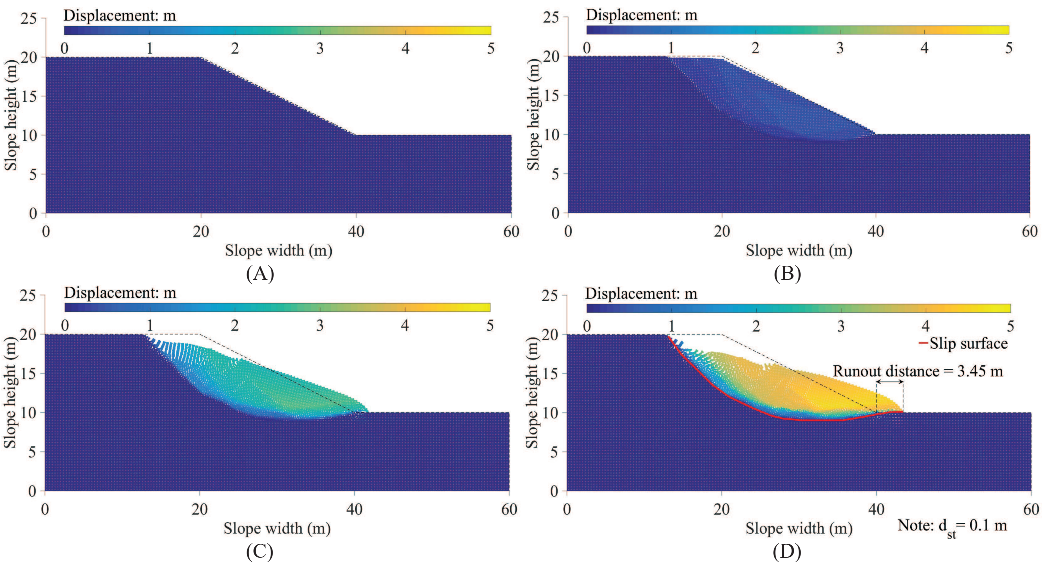

Figure 4. Deformed slope geometry of a typical failed slope sample at (A) t = 0 sec, (B) t = 1 sec, (C) t = 3 sec and (D) t = 6 sec (final stage).

5 Statistical Analysis

In this section, statistical analyses of landslide consequence, including runout distance and sliding mass volume are performed using results from the RSPH simulation. A MCS sample is considered as failed sample when the maximum soil displacement in the slope during landslide process is greater than d_{st} = 0.1 m. Under such a definition, 1111 failed samples are identified among all the 10,000 MCS samples. Landslide occurrence probability P_f is therefore calculated as 11.11 %.

5.1 Landslide runout distance

The histogram of landslide runout distance of failed samples is shown in Figures 5 (A), where x coordinate is runout distance and y coordinate is the normalized frequency. In Figure 5 (A), the runout distance of failed samples is with a mean of 1.85 m and a standard deviation of 2.00 m. The runout distance values are mostly within the range of 0 m to 5 m and may reach up to 13.12 m. It can be seen that, as runout distance increases, the normalized frequency firstly increases slightly and then decreases. Figure 5 (B) illustrates the exceeding probability of landslide runout distance of all MCS samples, where x coordinate is runout distance and y coordinate is the probability that the runout distance is greater than a given distance. It is shown that as the runout distance increases, the exceeding probability decreases. Figure 5 (B) provides a quantitative tool for decision making in engineering practice of landslide risk assessment and management. For example, if the acceptable failure probability is 0.1 %, which corresponds to a landslide runout distance of 8.73 m from the slope toe according to Figure 5 (B), any usage of the lands within 8.73 m from the slope toe should be evaluated with cautions. If there is a building situated 5 m away from slope toe, the probability that landslide sliding mass affects this building is 0.9 % based on Figure 5 (B), which is not acceptable if a target failure probability is 0.1 %

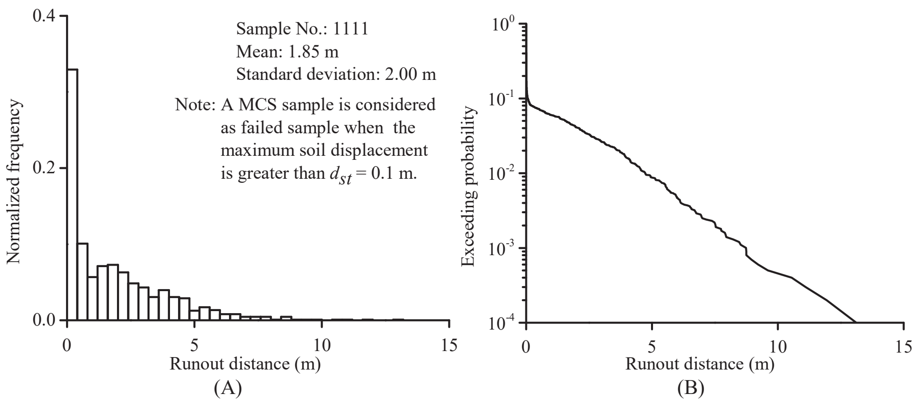

Figure 5. (A) Histograms of the runout distance of failed samples and (B) exceeding probability of the runout distance.

5.2 Sliding mass volume

Statistical analyses of sliding mass volume are performed using results from the RSPH simulation. A SPH particle is considered sliding when its displacement from SPH simulation is greater than d_{st} = 0.1 m. The sliding mass volume is then quantified as a product of the number of sliding particles and the area represented by each SPH particle in a two-dimensional simulation. In this study, the sliding mass volume is normalized by the triangular area of the slope (i.e., a slope with a height of 10 m and a width of 20 m), resulting in a normalized volume of sliding mass V_s.

The histogram of the normalized volume of sliding mass V_s of failed samples is illustrated in Figures 6 (A). It is shown that the normalized frequency firstly increases and then decreases as V_s increases. The V_s for the failed samples is with a mean of 1.25 and a standard deviation of 0.55. Most failed samples are in the range of 0.5 to 2, with the maximum value up to 3.59. The exceeding probability of the normalized volume of sliding mass V_s with d_{st} = 0.1 m is illustrated In Figure 6 (B). As V_s increases, the exceeding probability firstly remains more or less constant within a V_s range of [0, 0.75] and then decreases. Similar to Figures 5, Figure 6 can be used as a quantitative tool for decision making in engineering practice of landslide risk assessment and management.

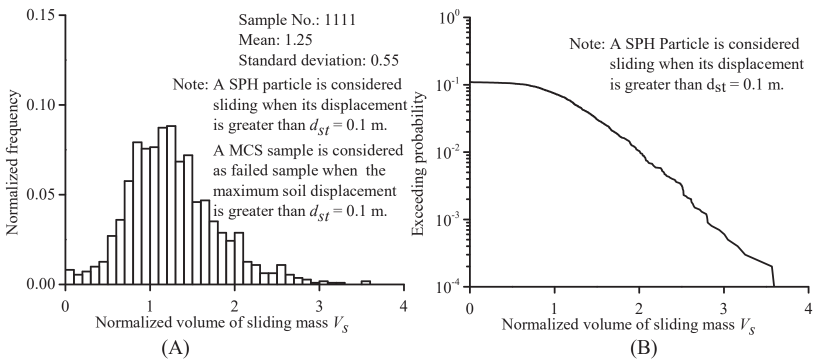

Figure 6. (A) Histograms of the normalized volume of sliding mass Vs of failed samples and (B) exceeding probability of the normalized volume of sliding mass Vs.

6 Conclusions

This paper developed a Monte Carlo simulation-based approach for the quantitative risk assessment of landslides, in which random field theory is combined with SPH to simulate large soil deformation and the whole process of a landslide. The proposed RSPH method is illustrated using a slope example. It is shown that the proposed RSPH method can provide reasonable estimates of landslide occurrence probability, landslide runout distance and volume of sliding mass, leading to a proper quantification of the landslide risk. Statistical analysis has been performed on the landslide runout distance and sliding mass volume, based on which the landslide warning system and corresponding mitigation measures can be developed.

Acknowledgments

The work described in this paper was supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. 8779012 (T22-603/15N)) and a grant from City University of Hong Kong (Project No. 7005040). This work utilized the High Performance Computer Cluster managed by the College of Science and Engineering of City University of Hong Kong. The financial support is gratefully acknowledged.

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