Proceedings of the XVIII ECSMGE 2024
GEOTECHNICAL ENGINEERING CHALLENGES
TO MEET CURRENT AND EMERGING NEEDS OF SOCIETY

ISBN 978-1-032-54816-6
DOI 10.1201/9781003431749-355

ECSMGE 24
XVIII EUROPEAN CONFERENCE
ON SOIL MECHANICS AND
GEOTECHNICAL ENGINEERING

Internal erosion initiation in gap-graded soils: A 3D microstructure assessment using convolutional autoencoders

Initiation de l'érosion interne dans les sols à granulométrie discontinue: Une évaluation de la microstructure 3D à l'aide d'autoencodeurs convolutifs

J. Qi, N. Yousefpour*, G. Narsilio
Department of Infrastructure Engineering, The University of Melbourne, Parkville, Australia

M. Pouragha
Department of Civil and Environmental Engineering, Carleton University, Ottawa, Canada

**negin.yousefpour@unimelb.edu.au*

ABSTRACT: Internal erosion in gap-graded soils is a major risk faced by earth dams and levees. However, the understanding of internal erosion mechanisms, especially at the particle scale, is still limited. This research couples the Discrete Element Method (DEM) with Computational Fluid Dynamics (CFD) to simulate the internal erosion (suffusion) process in gap-graded soil samples and further train Artificial Intelligence (AI)/Deep Learning (DL) algorithms to identify subtle patterns and anomalies related to internal erosion initiation. A time-lapse micro-structure visualisation approach is introduced using 3D voxelization of soil elements under internal erosion. Particle-scale parameters such as particle and flow velocity, number of contacts, contact forces etc are extracted from the CFD-DEM simulations throughout the internal erosion process forming time-series tensors used to train the AI models. The Autoencoder models with 3D Convolutional Neural Network (CNN) layers as encoder and decoder are developed to investigate the micro-scale patterns within the particle-fluid assembly together with the variations and anomalies throughout the erosion process. Using Sequential Training framework, anomalies within the data are detected by Convolutional Autoencoder models to identify the locus and time of internal erosion initiation. In addition, the micro-mechanisms during the initiation of internal erosion such as fine particle migration and contact loss are investigated. The 3D voxelization approach for internal erosion micro-mechanism visualisation can be integrated with advanced imaging techniques (e.g., micro-computed tomography) for early detection of internal erosion in future.

RÉSUMÉ: L'érosion interne dans les sols à granulométrie écartée représente un risque majeur pour les barrages en terre et les digues. Cependant, la compréhension des mécanismes d'érosion interne, en particulier à l'échelle des particules, reste limitée. Cette recherche couple la Méthode des Éléments Discrets (DEM) avec la Dynamique des Fluides Computationnelle (CFD) pour simuler le processus d'érosion interne (suffusion) dans des échantillons de sol à granulométrie écartée et pour entraîner davantage les algorithmes d'Intelligence Artificielle (IA)/Apprentissage Profond (AP) afin d'identifier des modèles subtils et des anomalies liées à l'initiation de l'érosion interne. Une approche de visualisation micro-structurale en accéléré est introduite en utilisant la voxelisation 3D des éléments de sol sous érosion interne. Des paramètres à l'échelle des particules tels que la vitesse des particules et du flux, le nombre de contacts, les forces de contact, etc., sont extraits des simulations CFD-DEM tout au long du processus d'érosion interne pour former des tenseurs en série temporelle utilisés pour entraîner les modèles d'IA. Des modèles d'Autoencodeurs avec des couches de Réseau Neuronal Convolutif (CNN) 3D comme encodeur et décodeur sont développés pour étudier les modèles microscopiques au sein de l'assemblage particule-fluide ainsi que les variations et anomalies tout au long du processus d'érosion. En utilisant le cadre de Formation Séquentielle, les anomalies dans les données sont détectées par des modèles d'Autoencodeur Convolutif pour identifier le lieu et le moment de l'initiation de l'érosion interne. De plus, les micro-mécanismes lors de l'initiation de l'érosion interne tels que la migration des particules fines et la perte de contact sont étudiés. L'approche de voxelisation 3D pour la visualisation des micro-mécanismes d'érosion interne peut être intégrée avec des techniques d'imagerie avancées (par exemple, la micro-tomographie informatisée) pour la détection précoce de l'érosion interne à l'avenir.

Keywords: DEM-CFD; internal erosion; convolutional neural networks (CNN); autoencoder; anomaly detection; deep learning; microstructure visualisation.

1 INTRODUCTION

Internal erosion is a typical issue faced by earth dams and levees, posing a significant risk to public safety and the economy. This phenomenon frequently occurs in gap-graded soils subjected to certain hydraulic and mechanical conditions. The initiation and development of internal erosion are mainly influenced by three factors: (a) particle gradation, (b) hydraulic condition, and (c) mechanical state (Brown & Bridle, 2009). In this context, the internal erosion has been studied through field monitoring (Cai et al., 2020; Chen et al., 2018), laboratory tests (Planès et al., 2016), numerical simulations (Tran et al., 2017), and data-driven analysis (Fisher et al., 2016; Yousefpour & Fazel Mojtahedi, 2023). Internal erosion usually initiates from imperceptible transport of fine particles at the pore scale with no evident signs and gradually develops into catastrophic dam breaches, which highlights the necessity of insight into the particle scale behaviours and their link to the macro-scale/field observations.

This study couples the Discrete Element Method (DEM) with Computational Fluid Dynamics (CFD) to simulate the internal erosion process in gap-graded soils, simulating the suffusion mechanism (Qi et al., 2022). 3D voxelization of the gap-graded soil was conducted with associated particle-scale parameters stored in the voxels as the input for the DL model. The Autoencoder models with 3D Convolutional Neural Network (CNN) layers as encoder and decoder are developed to investigate the micro-structure patterns within the particle-fluid assembly. A Sequential Training framework is introduced for Dl models to detect anomalies within the time-series of 3D particle-scale tensors for an assessment of locus and time of internal erosion initiation.

2 METHODOLOGY

2.1 CFD-DEM simulation

The coupled CFD-DEM simulations are performed to assess the internal erosion initiation process in gap-graded soil driven by a range of hydraulic gradients. A gap-graded sand sample with a Fine Content (FC) of 25% is selected for the simulation. The sample gradation and mass fractions for the grain sizes are provided in Table 1.

Table 1. Soil sample gradation and mass fractions.

Particle Group	Diameter	Finer %	Mass %
D1	3.43	62.5%	37.5%
D2	2.36	25.5%	37.5%
D3	0.36	12.5%	12.5%
D4	0.30	0	12.5%

The 3D CFD-DEM model of the gap-graded sand is created within a cylindrical shell (D=15mm, H=25mm). The time step of DEM is set to be 5e-7s for the stability of the calculation. For the first step, the particles are randomly generated at the top of the cylinder with predefined mass fractions and then settled to the bottom under gravity as shown in Figure 1. The generated dry samples are then compacted by a top plate to achieve a target sample density before saturation.

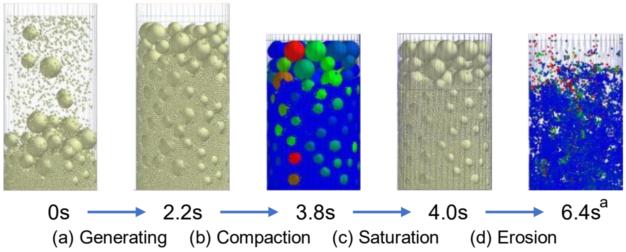

Figure 1. CFD-DEM model (a) Sample generating, (b) sample compaction to target porosity, (c) saturation and stabilization of compacted sample, (d) internal erosion.
[a] Coarse particles are hidden at t=6.0s for better visualization.

The compacted dry sample is then coupled with CFD under static hydraulic pressure for saturation. Both the DEM and CFD simulations continue to reach equilibrium during the saturation process. For the erosion stage, the plate on the top is replaced by a mesh that is only permeable to the fine particles. The hydraulic pressure of the outlet is set to 0, while that of the inlet is fixed to a value that applies a hydraulic gradient to the whole sample. The hydraulic pressure is linearly increased from 0kPa at t=4.0s to 100kPa at t=5.5s, during which fine particles are gradually eroded from the pore space between coarse particles. The eroded particles are deleted when they exit the top mesh.

2.2 Particle-scale data and 3D microstructure representation

The CFD-DEM simulation outputs are extracted in a high temporal resolution of 0.01s, which produces abundant particle-scale data. This data includes time-lapse tensor of particle velocity, contact force, contact number etc, which can reflect the subtle changes in interaction and migration of particles during internal erosion. However, this data could not require pre-processing before using as an input for DL models.

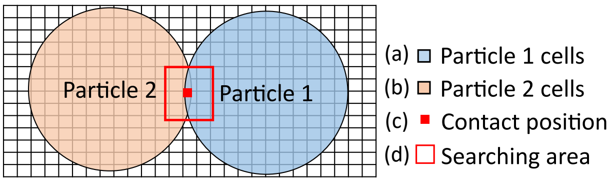

Figure 2. Particle data representation (a)&(b) cells with information from particle 1 &2, (c) contact position of two particles, (d) area to search for the contact cells.

To facilitate such purpose, a voxelization algorithm is developed to convert the particle-scale data into 3D matrix (tensor) representations. Voxels are defined using grids within the particle-fluid assembly domain. Each voxel is occupied by particles and fluid. The relevant particle-scale data are assigned to the respective DEM voxels, including particle velocity, contact force, contact number etc (Figure 2). As coarse particles are intact during suffusion, only fine particle parameters are considered in this process.

The voxels for storing the contact information are detected within a domain centred at the contact position by comparing the voxel-particle distance and the particle radius. With the particle information stored in the voxels, the constructed 3D matrices serve as the input for the subsequent Machine Learning models.

2.3 Deep learning approach

Convolutional Neural Networks (CNN) have been proven powerful in capturing/extracting features from image data (Tang et al., 2022). Also, Autoencoders have been successfully used for unsupervised anomaly detection for problems where normal (true) versus anomaly (fake) data is not known apriori (Yousefpour & Fazel Mojtahedi, 2023). Considering the 3D particle-scale data structure from CFD-DEM, a 3D Convolutional Autoencoder (CAE) architecture is deemed as a viable architecture to extract spatial-temporal patterns and anomalies related to subtle microstructure changes in the soil sample around the initiation of erosion. In this problem, the sample 3D microstructure is visualised by the generated particle-scale tensors. These time-series tensors are treated as image data for the CAE algorithm. The encoder compresses the input data into latent representations while the decoder reconstructs the input from the latent space. The encoder and decoder are constructed from 3D Convolutional layers and the necessary max pooling or deconvolutional layers as depicted in Figure 3. The CAE model learns the reconstruction error distribution over the training dataset and then detects anomalies within the test dataset using a set error threshold. A data point is recognised as an anomaly if its reconstruction error is larger than this threshold.

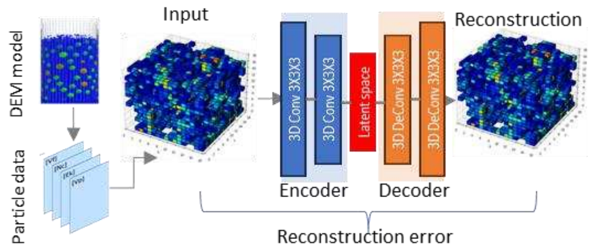

Figure 3. 3D CNN Autoencoder architecture.

2.4 Data division and sequential training

CFD-DEM outputs are extracted at a time step of 0.01sec, from 4.0sec to 6.4sec, generating a time-series of 240 tensors. Sequential Training is a systematic approach of Machine Learning (ML) training in consecutive steps, where the training database size grows linearly at each step, rather than using the entire dataset at once (Yousefpour & Fazel Mojtahedi, 2023). This approach has proven effective in detecting the initiation of internal erosion based on the evolution of the number and trend of anomalies. In this study, Sequential Training was conducted over eight stages. During each step, a distinct segment of the data was used for training followed by a non-overlapping segment for validation (see Figure 5).

3 RESULTS

3.1 Fine particle migration

To better capture the internal erosion process, only a fraction of the whole CFD-DEM located at the top of the sample where the most intensive migration of fine particles happened is incorporated to train the CAE model. The particle velocity tensors are converted to a binary scale, such that voxels with particle velocity are represented as 1. Visualizing two slices of the binary tensors at t=4.1s, shown in Figure 4(a) and t=6.2s, shown in Figure 4(b) reveals the patterns of fine particles migration. It's also observed that the scatter within the selected region gets denser as the fine particles gradually migrate from lower positions to the top. In particular, potential preferential erosion paths that fine particles take through the pore space between coarse particles are captured.

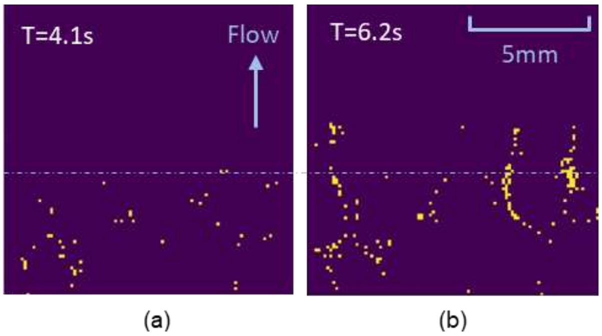

Figure 4. Binary particle velocity slices (a) before suffusion (T=4.1s) (b)after suffusion (T=6.2s).

3.2 Anomaly detection

The Convolutional Autoencoder model is trained using the binary particle velocity tensors prior to obvious internal erosion initiation in the sample (mass loss). The reconstruction errors are calculated for tensors within the test dataset after each training step. The number of detected anomalies from the testing data is recorded as the internal erosion evolves after the application of hydraulic gradient at t=4.0s as shown in Figure 5. The number of anomalies stays constant at the initial steps (from 4.0s to 5.2s) with all the test data being recognised as anomalies, meaning the fine particle velocity patterns during this stage are largely different from the test dataset and internal erosion did not happen at this stage. After t = 5.2s, the number of anomalies decreases abruptly, which can indicate a sudden pattern change of the fine particles. Between 5.2s and 5.6s, the number of anomalies starts to converge to a constant value. This trend shows that the training dataset is more representative of the test dataset patterns (therefore fewer anomalies are identified) and be an indicative of the approximate time of internal erosion initiation. Based on the above observations, it can be inferred that internal erosion initiated between 5.2s and 5.4s.

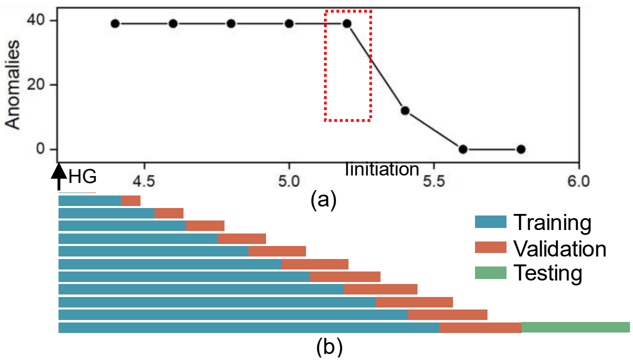

Figure 5. Anomaly detection across training stages (a) Number of anomalies detected from different training stages (b) sequential training stages.

4 CONCLUSIONS

This research investigates the initiation of internal erosion in gap-graded soils through a Convolutional Autoencoder deep learning algorithm trained using CFD-DEM simulations data.

Fine particle velocity data are visualized using a 3D voxelization method and converted to time-lapse binary tensors to assess the internal erosion patterns during the initiation phase. The subtle changes in the microstructure of the soil element and migration patterns of the fine particles are captured using this approach.

The CAE model trained with the time-series of particle-scale tensors based on the sequential training framework shows a sudden drop followed by the convergence trend close to the initiation of internal erosion. This shows that the 3D voxelisation approach for internal erosion micro-mechanism visualisation can be potentially integrated with advanced imaging techniques (e.g. micro-CT) for early detection of internal erosion in future studies.

ACKNOWLEDGEMENTS

The authors are grateful for the financial support of the University of Melbourne's Early Career Research Grant and the China Scholarship Council Scholarship.

REFERENCES

Brown, A., & Bridle, R. (2009). Report on the European working group on internal erosion, St. Petersburg. *Dams and Reservoirs*, *19*(3), 133–136. https://doi.org/10.1680/dare.2009.19.3.133.

Cai, Y., Cheng, H., Wu, S., Yang, Q., Wang, L., Luan, Y., & Chen, Z. (2020). Breaches of the Baige Barrier Lake: Emergency response and dam breach flood. *Science China Technological Sciences*, *63*(7), 1164–1176. https://doi.org/10.1007/s11431-019-1475-y.

Chen, C.-Y., Chen, S.-C., Chen, K.-H., & Liu, Z.-H. (2018). Thermal monitoring and analysis of the large-scale field earth-dam breach process. *Environmental Monitoring and Assessment*, *190*(8), 483. https://doi.org/10.1007/s10661-018-6869-y.

Fisher, W. D., Camp, T. K., & Krzhizhanovskaya, V. V. (2016). Crack Detection in Earth Dam and Levee Passive Seismic Data Using Support Vector Machines. *Procedia Computer Science*, *80*, 577–586. https://doi.org/10.1016/j.procs.2016.05.339.

Planès, T., Mooney, M. A., Rittgers, J. B. R., Parekh, M. L., Behm, M., & Snieder, R. (2016). Time-lapse monitoring of internal erosion in earthen dams and levees using ambient seismic noise. *Géotechnique*, *66*(4), 301–312. https://doi.org/10.1680/jgeot.14.P.268.

Qi, J., Yousefpour, N., Narsilio, G., & Pouragha, M. (2022). Initiation of Internal Erosion in Earth Dams: A Particle-

Scale Computational Approach. *Australian Geomechanics Society 2022 Victoria Symposium*.

Tang, P., Zhang, D., & Li, H. (2022). Predicting permeability from 3D rock images based on CNN with physical information. *Journal of Hydrology*, *606*. https://doi.org/10.1016/j.jhydrol.2022.127473.

Tran, D. K., Prime, N., Froiio, F., Callari, C., & Vincens, E. (2017). Numerical modelling of backward front propagation in piping erosion by DEM-LBM coupling. *European Journal of Environmental and Civil Engineering*, *21*(7–8), 960–987. https://doi.org/10.1080/19648189.2016.1248794.

Yousefpour, N., & Fazel Mojtahedi, F. (2023). Early detection of internal erosion in earth dams: combining seismic monitoring and convolutional AutoEncoders. *Georisk*.