ASSESSING GROUND SETTLEMENT USING COMPUTER VISION AND ARTIFICIAL INTELLIGENCE IN GEOTECHNICAL ENGINEERING

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Research note: This manuscript proposes a methodology. No experimental dataset or measured results were supplied; therefore, no numerical findings are claimed.

Abstract

Ground settlement is an important geotechnical concern because excessive or differential deformation can affect the serviceability and safety of foundations and structures. This paper outlines a proposed methodology for combining computer vision with machine-learning techniques to monitor and estimate settlement in laboratory soil tests. Sequential digital images are used to track surface markers, while camera calibration converts image displacement into physical units. Loading conditions and relevant soil properties may then be used as input variables for a regression model. Root mean square error is proposed as one measure for evaluating predictions against independent measurements. The work is methodological and does not report experimental results, because no test data were provided. The proposed workflow requires validation against conventional displacement measurements and careful control of camera movement, lighting, perspective and soil-surface conditions.

Keywords: artificial intelligence; computer vision; geotechnical engineering; ground settlement; machine learning.

1. Introduction

Ground deformation under external loading is a central topic in geotechnical engineering. Settlement of soil beneath foundations may lead to serviceability problems, differential movements and damage to structures. Conventional assessment relies on laboratory testing, field instrumentation, geodetic surveying

and numerical modelling. These methods remain essential, but digital image analysis may complement them by enabling non-contact observation of surface movement.

Artificial intelligence (AI) and machine-learning approaches have increasingly been investigated for geotechnical prediction tasks. Their performance depends on representative data, suitable input variables and validation against reliable measurements [1–3]. This paper proposes a laboratory workflow in which computer vision estimates visible soil-surface displacement and a regression model explores its relationship with loading and soil parameters.

2. Aim and objectives

The aim is to formulate a reproducible method for estimating soil-surface settlement from sequential images and evaluating whether machine learning can support settlement prediction. The objectives are to: (i) capture images during staged loading; (ii) detect and track reference markers; (iii) calibrate image coordinates to physical units; (iv) compare image-derived displacement with an independent measurement method; and (v) evaluate a regression model using held-out data.

3. Proposed methodology

3.1. Laboratory setup and image acquisition

A soil specimen is placed in a rigid test container and subjected to controlled loading stages. A camera is mounted on a stable support, with lighting and camera settings kept as consistent as possible. Reference markers or a suitable surface texture are recorded before loading and at defined intervals during the test. The test should also record soil type, moisture content, specimen dimensions, applied pressure and elapsed time. An independent displacement gauge or another validated measurement method is recommended for comparison.

3.2. Image displacement and calibration

Let a tracked point have image coordinates (x_0, y_0) in the initial image and (x_1, y_1) in a later image. The pixel displacement is $\Delta x = x_1 - x_0$ and $\Delta y = y_1 - y_0$. If

the imaging geometry is calibrated and the scale is valid for the region of interest, vertical displacement magnitude can be estimated as $s = k_\gamma |y_1 - y_0|$, where k_γ is the vertical scale in physical units per pixel. A simple scale factor is not sufficient when perspective, lens distortion, camera movement or out-of-plane motion is significant; these effects must be controlled or corrected.

3.3. Machine-learning formulation

A regression model may be formulated as $s_pred = f(q, w, e, H, t, \Delta y)$, where q is applied pressure, w is soil moisture content, e is void ratio, H is specimen or layer thickness, t is elapsed time, and Δy is image-derived vertical displacement. Candidate models include linear regression, random forest regression, support vector regression and neural networks. Model complexity should be selected according to the amount and quality of available data rather than assumed in advance.

3.4. Evaluation

Predictions should be compared with independent reference measurements. One suitable metric is root mean square error (RMSE): $RMSE = \sqrt{[(1/n) \Sigma_{i=1}^{n} (s_i - \hat{s}_i)^2]}$, where s_i is measured settlement, $\hat{s}_i$ is predicted settlement and n is the number of evaluated observations. Training and test data should be separated to reduce the risk of reporting overly optimistic performance. If measurements from the same specimen are strongly correlated, splitting should be performed by test or specimen where feasible.

4. Expected contribution and limitations

The proposed workflow may support non-contact tracking of soil-surface movement, systematic processing of image sequences and a structured comparison of machine-learning models. It is not yet an experimentally validated system. Accuracy may be affected by image resolution, lighting, marker visibility, calibration quality, camera stability and the representativeness of the training dataset. Surface movement measured from images may not fully represent internal

soil deformation. Consequently, the approach should complement rather than replace established geotechnical tests and instrumentation.

5. Conclusion

This paper presents a proposed computer-vision and machine-learning workflow for assessing ground settlement in laboratory geotechnical tests. Sequential images can be used to estimate surface displacement when image geometry is appropriately calibrated, while regression models can be evaluated against independent measurements. Further work should collect repeatable laboratory data, quantify measurement uncertainty and validate model performance across soil types and loading conditions. No experimental results are claimed in this paper.

References

[1] Application of artificial intelligence in geotechnical engineering: A state-of-the-art review. Earth-Science Reviews, 228 (2022), 103991. https://doi.org/10.1016/j.earscirev.2022.103991

[2] Niu, G., He, X., Xu, H., & Dai, S. (2024). Tunnelling-induced ground surface settlement: A comprehensive review with particular attention to artificial intelligence technologies. Natural Hazards Research, 4(1), 148–168. https://doi.org/10.1016/j.nhres.2023.11.002

[3] Sheil, B., et al. (2026). Artificial intelligence transformations in geotechnics: Progress, challenges and future enablers. Computers and Geotechnics, 189, 107604. https://doi.org/10.1016/j.compgeo.2025.107604