Damage identification in concrete using multiscale computational modeling and convolutional neural networks

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Concrete is a composite material with heterogeneities across multiple length scales. Degradation of concrete due to external loadings starts with diffuse microcracking, followed by damage localization that eventually leads to structural failure. Identification of damage at an early stage of degradation reduces the costs associated with maintenance of the structure. Weak changes can be detected using diffuse ultrasonic waves (so-called Coda waves). In this contribution, a virtual testing environment for the assessment of concrete damage using coda waves is presented. The virtual test environment combines multiscale computational modeling of concrete damage, modeling of ultrasonic wave propagation, and supervised learning. At the scale of mortar material, microcrack growth is modeled using a combination of continuum micromechanics and linear elastic fracture mechanics. The micromechanics model is incorporated into a reduced-order Lippmann-Schwinger based mesomodel for concrete. Synthetic concrete specimens at various damage levels are generated using the multiscale damage model and subsequently these specimens are subjected to wave propagation analysis using the rotated staggered-grid-finite-difference scheme. A convolutional neural network (CNN) based supervised learning framework is further employed to classify damage given the coda signals.

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1 Virtual concrete lab concept for damage identification

For a better understanding of the effect of damage in concrete on the evolution of coda signals at the specimen scale, we generated a ‘virtual concrete lab’ environment, whose methodology is described as follows. First a virtual concrete specimen of standard AB16, generated from the measured aggregate size distribution, is subjected a uniaxial compression load. Damage evolution due to distributed microcracking is modeled using the multiscale reduced order model for concrete proposed by the authors (see [1]). From the reduced order simulation (ROS), 12 concrete mesostructure snapshots at different damage levels are further subjected to forward wave propagation simulations using the rotated staggered finite-difference solver [3]. Finally, a CNN based damage classifier is developed to identify damage of the concrete specimen based on the simulated coda signals.

2 Multiscale reduced-order simulation of concrete

The reduced-order multiscale model is a synthesis of continuum micromechanics, fracture mechanics defined at the microscale (mortar) that is coupled to a reduced order Lippmann-Schwinger formulation at the mesoscale (concrete). The interaction among scales is performed via Localization and Homogenization procedures. See Fig. 1 for a schematic illustration of the multiscale model. Damage in the mortar matrix is described by the growth of three pre-existing microcracking families. The growth of microcracks is governed by the linear elastic fracture mechanics framework and the homogenization of damaged mortar matrix at microscale is performed using the Interaction Direct Derivative scheme [2]. The proposed model is further calibrated and validated using experimental data on a virtual concrete specimen standard AB16 of size 10 cm. The validation result is summarized in figure 2 left box. From the reduced order simulation, 12 simulated snapshots (3D voxel state) are extracted and grouped into three distinct classes, namely ‘Phase 1’ (green markers), ‘Phase 2’ (mustard markers), and ‘Phase

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3 (red markers). In the regime denoted as ‘Phase 1’, microcracks close perpendicular to the loading direction, resulting in a slight increase in the apparent stiffness. The regime ‘Phase 2’ is characterized by growth of diffusively distributed microcracks, also called ‘failure precursors’. In ‘Phase 3’, multiple mesoscopic cracks parallel to the loading direction are formed due to the coalescence of microcracks before reaching the ultimate strength.

3 CNN based damage classifier

Numerical wave propagation is performed on each of the 12 mesostructure snapshots. A rotated staggered-grid finite difference scheme is used to propagate a seismic wave field in the forward simulations [3]. A total of 3 optimal source locations are used to induce a body force based wavelet with a center frequency of 85 kHz and 9 sensors are employed to record displacement components (x, y, and z) over a duration of 2 ms. In total, a dataset, consisting of 972 time series signals is acquired. Given the simulated ultrasonic data, we aim to use supervised learning to identify the damage state of a concrete specimen given a coda signal. Before being fed to a Convolutional Neural Network (CNN) classifier, each coda time series signal (denoted as ‘data point’) is re-shaped into a 2D matrix of dimension 200 × 200 and is assigned to one of three classes. We use a feed forward CNN based classifier, whose architecture is described in Fig. 2 right box b. It is observed that the performance of the CNN using the full dataset is satisfactory, with an overall accuracy of 85% (Fig. 4c). From the confusion diagram, predictions of three phases are obtained with satisfactory accuracy. Moreover, there is no false prediction between the classes “Phase 1” (elastic deformation) and “Phase 3” (near peak regime), while there is still a marginal error in distinguishing diffuse microcracking and microcrack coalescence (near peak regime), with approximately 15% of misclassification.

Fig. 2: Left box: a) Visualization of the reduced-order concrete specimen (consists of 72 clusters) obtained from the k-means cluster algorithm. b) Stress-strain behavior. The 12 load levels at which the microstructure snapshots are extracted for machine learning are marked by colored dots. c),d),e),f) opening of vertically oriented microcracks in the mortar matrix at 4 different loading levels (25.77, 37.05, 47.06, and 63.41 MPa), red color indicates active microcracking regions. Right box: a) Deep learning CNN architecture used for damage identification: The input is a time-series image and the output is the material state. b) Confusion matrix of the classifier, c) Training and validation accuracy and loss of the classifier up to 200 epochs.

4 Conclusion

In this contribution, a virtual concrete lab environment for damage classification in concrete, is presented. This computational approach involves a synthesis of computational mechanics, multiscale modeling and machine learning for the identification of early-stage damage in concrete.

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