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IDENTIFYING DAMAGE IN CONCRETE USING CODA SIGNALS, MULTI-SCALE SIMULATIONS AND MACHINE LEARNING

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Abstract. The economic performance and to a certain degree the stability of modern society depend on the reliability and durability of concrete infrastructure. Therefore, maintenance of infrastructure remains one of the primary core tasks. If damage at an early stage is detected and precautionary measures are applied, maintenance costs can be significantly reduced, and lives can be saved by preempting failure. Concrete damage at an early stage is characterized by microcracks, much smaller than the aggregate size whose detection is not possible using conventional ultrasonic (US) monitoring. However, the multiple-scattered late arriving US signals (i.e., coda signals) contain rich information that detects weak changes. While the high precision and sensitivity of the coda signals can be used to identify precursor damage events that precede catastrophic failure, extracting this information is challenging. In this contribution, a multi-scale approach combining computational modeling and machine learning techniques are used to simulate the identification of damage level in concrete specimens using coda wave interferometry. Concrete damage is simulated using a reduced order multiscale model that combines continuum micromechanics, the integral form of the Lippmann-Schwinger equation solver for the strain field at the mesoscale and machine learning. Data from wave propagation simulations are used to compute the relative velocity change i.e. a measure of weak change in the material using coda wave interferometry. The results of the analysis and the potential for estimating precursor damage directly from ultrasonic signal measurements are discussed.

1 Introduction

Over their service life, concrete structures experience a gradual degradation due to exposure to various environmental and mechanical loads. These factors foster the growth of existing defects in concrete, and without proper maintenance, microcrack growth may lead to microcrack coalescence and crack localization, ultimately causing a complete loss of the structure's load-bearing capacity. Detecting early-stage degradation in concrete structures is crucial to reducing maintenance and repair costs. One potential solution for early detection of changes to the material microstructure is the evaluation of diffuse ultrasonic waves using Coda Wave Interferometry (CWI) [11]. CWI is a seismological technique that utilizes the late arriving diffuse ultrasonic signals, called coda signals. These coda signals, due to multiple scattering and extended stay in the material, carry valuable information about the concrete microstructure, allowing for the extraction of subtle material changes. However, the high sensitivity of diffuse ultrasonic signals presents a challenge in accurately translating the variations into concrete damage levels. Numerous experimental investigations have explored the potential of CWI to quantify load-induced damage in concrete. Nevertheless, issues arise in laboratory environments, particularly regarding damage quantification and effect discrimination. To address these challenges, numerical simulations can provide insights into the physical phenomena and establish a quantitative relationship between damage and coda signal variations. In this contribution, we present a computational framework that simulates both load-induced distributed damage and wave propagation in a concrete specimen subjected varying levels of mechanical loads. Subsequently, we evaluate the correlation of the coda signal variations evaluated from the wave propagation simulations to the evolution of precursor damage in the specimen. Figure 1 provides a schematic representation of this workflow.

2 Simulation of load induced distributed damage in concrete

When subjected to uniaxial compression, concrete undergoes a complex damage process involving various intricate mechanisms operating simultaneously across different scales [14]. This complexity stems from the heterogeneous nature of concrete, spanning from the nanometer scale to the decimeter scale. At the microscopic scale (approximately 10^{-3} m), mortar comprises of a hardened cement matrix containing sand particles, pores, and microcracks as defects. At the meso-level, concrete is made of irregular coarse aggregates randomly dispersed within a mortar matrix. Consequently, under loading, concrete exhibits a highly disturbed stress field, leading to stress fluctuations that cause microcracks to deform and propagate, playing a significant role in the pre-peak behavior of concrete. Considering these microstructure details and their evolution induced by external loads is crucial from a modeling perspective. Hence, for simulating distributed damage in concrete, we adopted the reduced order multiscale modeling strategy proposed in [15]. Figure 2 provides a schematic representation of the multiscale model.

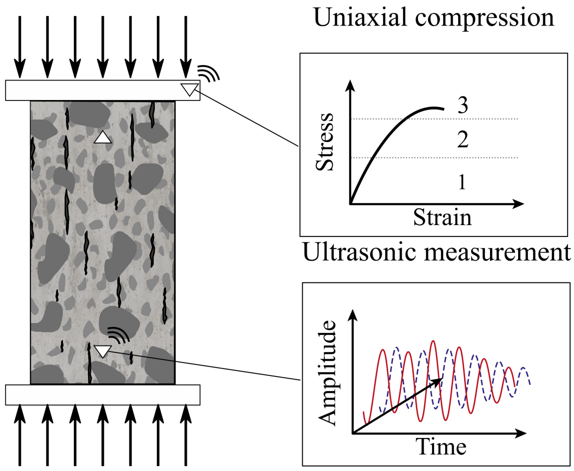


Figure 1: Schematic illustration of the virtual concrete laboratory for identifying damage in concrete using diiffuse ultrasonic signals.

2.1 Method

In a multiscale modeling framework, the main challenge lies in efficiently exchanging information between the scales. To overcome this challenge, two fundamental operations are employed: Localization and Homogenization. These operations play a crucial role in establishing a reliable link between the microscale details and the macroscale behavior of the material. By adopting a multiscale modeling approach, we can avoid relying solely on conventional empirical constitutive models, which may have limitations in accurately capturing the complex behavior of concrete. Instead, this method allows us to develop microstructure-property relationships, providing a deeper understanding of how the microstructure influences its overall mechanical response. However, when explicitly resolving the microstructure in a multiscale framework, the computational requirements can become prohibitively high. This is because, at each material point, a significant number of sub-problems need to be solved, which can be computationally demanding and time-consuming. To address this

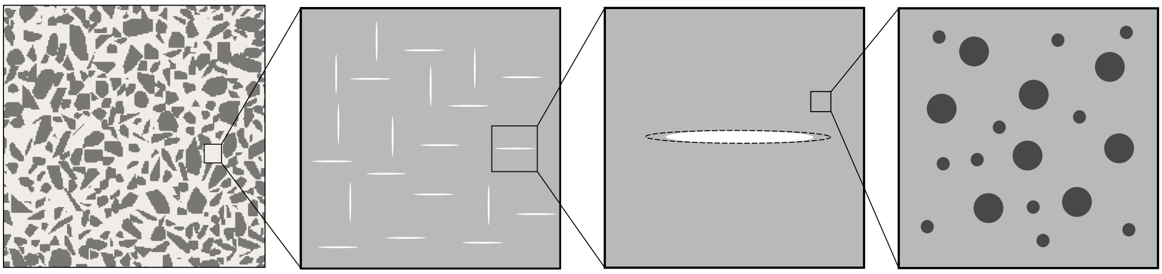


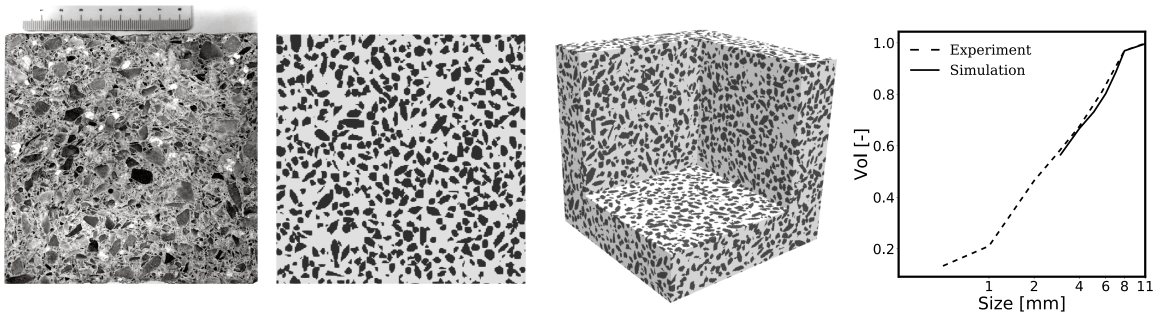
Figure 2: Schematic illustration of the multiscale model showing distributed penny-shaped microcracks and coarse aggregates embedded in the mortar matrix made of hardened cement paste and sand.

issue, model order reduction techniques can be employed. These techniques aim to reduce the complexity of the model while preserving its essential features. In the context of modeling concrete, our proposed multiscale approach adopts an unsupervised machine learning approach [5] for clustering regions of the specimen that are expected to behave in a similar manner i.e. to avoid redundancy in solving for the same material state in different parts of the specimen at the macroscopic scale. This method groups material points (voxels) based on the similarity of their mechanical behavior into clusters. By doing so, we simplify the modeling process and significantly reduce the computational effort. The Localization step is an essential part of the multiscale approach. Here, given the applied macroscopic strain, we compute the mesoscopic strain field using the Fast Fourier Transform (FFT)-based computational homogenization method [7]. The mesoscopic strain tensor represents the strain distribution at an intermediate scale between the microscopic and macroscopic levels.

Subsequently, the information obtained from the Localization step is transferred to the microscopic scale. At this scale, the evolution of microcrack topology is modeled using the framework of Linear Elastic Fracture Mechanics (LEFM) [4, 9, 12]. This allows us to capture the growth and propagation of microcracks, which are the contributing factors to damage evolution. The final step, Homogenization, focuses on understanding the impact of evolving microcracks on the material's overall mechanical properties. The presence of microcracks alters the effective secant stiffness tensor, which is a measure of the material's resistance to deformation. We calculate this effective stiffness tensor using the modified Interaction Direct Derivative (IDD) technique [15]. By integrating Localization and Homogenization procedures, our multiscale modeling framework bridges the gap between the microscale mechanics and the macroscopic response of the material under different loading conditions. This approach not only enhances our understanding of concrete behavior but also provides valuable insights for designing more durable and reliable structures.

2.2 Digital Concrete Twin

An essential component in our simulations is the digital representation of concrete. To create a highly realistic virtual specimen, we utilized PyCMG a computational tool that generates realistic concrete specimens [3]. This tool takes into account the measured size distribution of coarse aggregates and provides a geometrical description of each aggregate family, including size, aspect ratio, smoothness, and concave surface parameters. The generated mesomodel is periodic, which offers distinct advantages in computational homogenization and forward wave simulations, contributing to the accuracy of our results [3]. For our analysis, we considered concrete specimens with a size of 10 cm, following the standard AB8 specifications. A total of 37% coarse aggregate content was resolved with the minimum grain size of 3 mm. To ensure precision in our simulations, the high-fidelity concrete specimen was discretized



(a) (b) (c)

Figure 3: Digital concrete twin showing a distributed realistic aggregate distribution. a) Comparison of actual concrete slice with the digitally generated concrete mesostructure, b) 3D voxel representation of the digital concrete twin and c) comparison of aggregate size distribution

into 201^3 voxels of size 0.5 mm. The concrete twin is shown in Figure 3.

Model order reduction of the digital concrete twin resulted in 72 clusters: 64 clusters representing the mortar matrix and 8 clusters representing quartzitic aggregates. This reduction technique allows us to streamline the computational process while preserving critical material features [3]. To complete our analysis, we listed the material parameters for each constituent in Table 1. This mesoscopic approach significantly enhances our ability to simulate and analyze concrete's mechanical response in a computationally efficient manner, making it a valuable tool for designing and optimizing concrete structures.

The material and numerical parameters were determined following the guidelines outlined in [15]. It is essential to emphasize that the model's validity has been established through rigorous validation against experimental data. In our analysis, the microcrack parameters and material parameters of mortar matrix were adapted to match the material properties of concrete composition provided in [1] (concrete standard AB8 with cement type CEM I 42.5R with water/cement ratio of 0.45). In addition, a sub-model described in [6] is adapted to describe the stiffening effect related to microcrack closure observed in the elastic deformation regime [10]. As a result, a so-called closing pressure parameter $(P_c = 30MPa)$ has been introduced. The IDD parameters also have to be specified i.e. the cell aspect ratio and cell growth rate (see [15]), these are calibrated parameters that control microcrack distribution in the cementitious matrix. In our simulation, the values were set to $\frac{1}{18}$, and 3.5 respectively.

Microcrack radius a	0.0011 mm
Microcrack half thickness c	0.0001 mm
$\phi_{\text{crack-initial}}$	9.8%
g_f	0.875 N/mm

Table 2: Micromechanical model parameters. g_f is the microscopic fracture energy and $\phi_{\text{crack-initial}}$ is the initial microcrack volume fraction.

The microcrack parameters and the mechanical properties of the mortar matrix used in our numerical simulations are presented in Table 2. The microcrack parameters play a critical role in capturing the complex behavior of the con-

Material	Young's Modulus E (GPa)	Poisson's Ratio ν	Density ρ (kg/m^3)
Quartzitic Aggregate	84.6	0.12	2650
Mortar Matrix	30.1	0.19	2104
Concrete	48.03	0.15	2364

Table 1: Material parameters of quartzitic aggregate, mortar matrix and concrete standard AB8

crete at a microscopic level.

2.3 Simulation of Precursor Damage

The clustered virtual specimen is then subjected to a uniaxial compression test, with the strain increment set at 10^{-5}. The simulation yields a stress-strain curve, visually represented in Figure 4. It must be noted that the damage modeling framework is only valid as long as the microcracks are homogeneously distributed. Hence the simulation is not performed beyond the peak stress i.e. the compressive strength of the material.

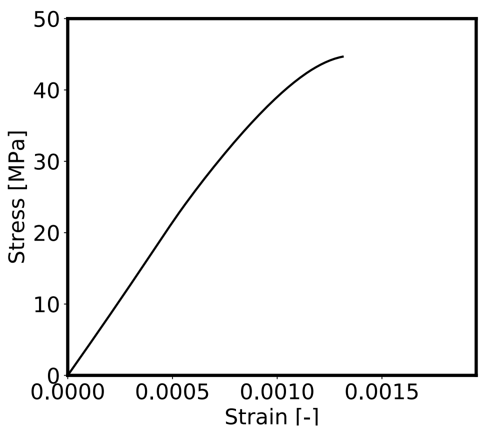


Figure 4: Simulated mechanical behavior of concrete due to uniaxial compression

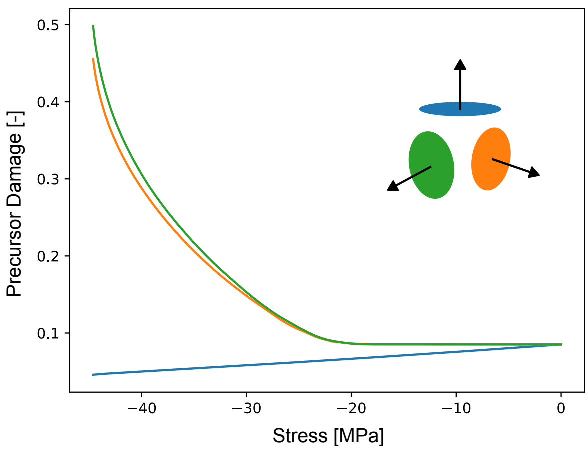


Figure 5: Evolution of precursor damage due to microcrack growth under uniaxial compression. Shown is the averaged contribution from three orthogonal microcrack families.

Figure 5 shows the evolution of the three microcrack geometries due to the applied loading. Precursor damage refers to the volume fraction of microcracks normalized by the total volume fraction of microcracks at peak stress (in our case around 44 MPa). At peak stress the precursor damage is 1. As seen in the figure the microcracks oriented in the horizontal direction i.e. whose normal is parallel to the loading direction, close. In contrast the microcrack families oriented in the vertical direction grow.

2.4 Coda Wave Interferometry

When presented with two ultrasonic signals acquired from a fixed source and a fixed receiver, Coda Wave Interferometry (CWI) can be applied to the coda sections of these signals, enabling an assessment of their similarity. Through this process, any alterations in the examined medium can be identified. Over the past few decades, several CWI methods have been proposed, most of which involve calculating velocity variation and cross correlation features. For our current analysis, we have chosen to utilize the stretching technique [8] due to its stability, regardless of the time-window chosen for evaluation.

To elaborate, given two signals, $u_u(t), u_p(t)$, that are evaluated within the time window $[t_1, t_2]$, the relative velocity change $\frac{dv}{v}$ is determined by finding the stretch factor ε that maximizes the cross-correlation of these two signals. This technique allows us to pinpoint any variations in velocity between the recorded signals and provides valuable insights into the changes occurring within the medium under examination.

$$
\begin{aligned}
\frac{dv}{v} &= \underset{\varepsilon\in\mathbb{R}}{\operatorname{argmax}}\, CC(\varepsilon) \\
&= \underset{\varepsilon\in\mathbb{R}}{\operatorname{argmax}} \frac{\int_{t_1}^{t_2} u_u(t) u_p(t(1+\varepsilon))\, dt}{\sqrt{\int_{t_1}^{t_2} u_u^2(t)\, dt \int_{t_1}^{t_2} u_p^2(t(1+\varepsilon))\, dt}},
\end{aligned}
\tag{1}
$$

here u_u and u_p denotes signals travelling through unperturbed and perturbed medium, respectively.

2.5 Results

Damaged concrete digital twins at various levels of precursor damage were subjected to wave propagation simulations. Simulated signals were extracted from selected virtual transducer pairs. For details regarding the wave propagation simulations see [2, 13, 16].

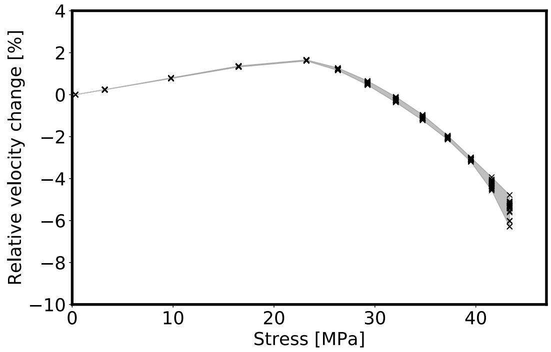


Figure 6: Relative velocity change vs. applied compressive stress

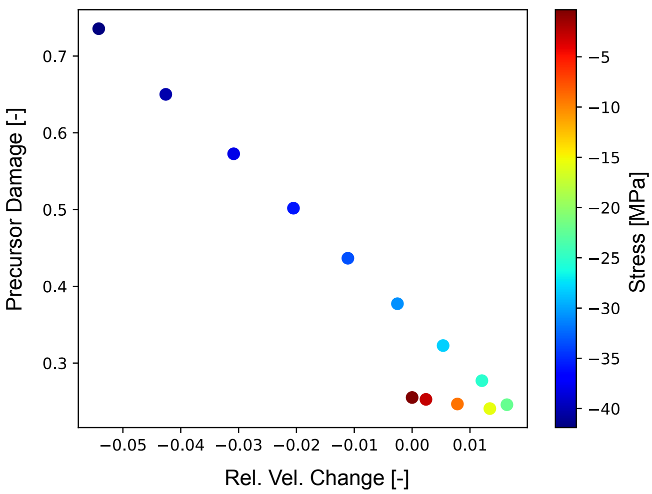


Figure 7: Precursor damage vs. relative velocity change

Figure 6 shows the correlation of $\frac{dv}{v}$ and the applied stress. Three stages can be identified. In the low loading levels upto $\approx 22MPa$, the simulation reproduces the typical increase in wave velocity typically seen in the experiment. With further increase in loading, we see a reduction of $\frac{dv}{v}$ at the rate of 0.0041 MPa^{-1} due to diffuse microcracking. Overall, the trend reproduced from the simulation is similar to the experimental range reported in [1]. Moreover, a linear correlation between $\frac{dv}{v}$ and the overall precursor damage can be seen in Figure 7 once the precursor damage growth occurs. The corresponding stress levels are shown in terms of the color of the plot markers.

3 Conclusions

This study presents a computational framework for assessing damage in concrete using diffuse ultrasonic waves. The approach involves performing mechanical simulations through a multiscale reduced order modeling methodology, followed by wave propagation simulations in the concrete specimen at different precursor damage levels. The recorded signals are then subjected to analysis using the CWI method, from which a relationship between relative velocity change and damage precursor is derived. Several key observations can be made based on the numerical results:

- A virtual environment for ultrasonic testing has been successfully established. The proposed methodology effectively reproduces experimentally observed phenomena, making it valuable for generating large synthetic datasets for data-driven damage classification.

- From the perspective of structural health monitoring, the CWI method enables the evaluation of global material degradation in concrete, assuming that the type of damage is known beforehand. It is essential to note that concrete exhibits high resistance to compression loads and can sustain a prolonged stage of microcracking under such conditions.

- Our analysis shows that there is a linear correlation between the evolution of precursor damage and the relative velocity change i.e. the ultrasonic signal feature. This finding can be used to establish material constants depending on the material compositions. These constants can then be used to directly predict the precursor damage level purely from ultrasonic signals.

- For future work, introducing material uncertainty into the computational framework is essential. This can be achieved by simulating additional concrete samples with varied grain size distribution, strength, and stiffness properties.

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