Concrete Characterization using Ultrasound and Physics-Informed Neural Networks

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Introduction

Rebound hammer

- Easy to use
- Need calibration curve
- Relatively low repeatability

Ultrasound pulse velocity

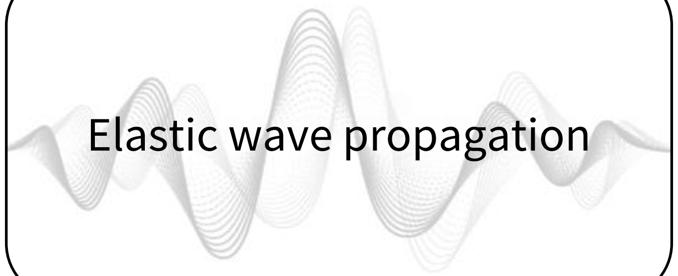
- Characterize subsurface material property
- Affected by contact conditions

Vision-based methods

- Fast and good for automation
- Only for surface open crack
- Not direct correlation with material properties

Introduction

Development of *in-situ* spatial dependent material characterization method



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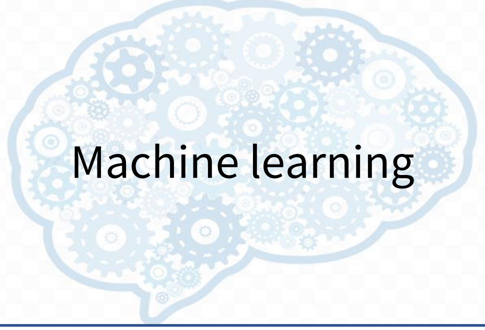


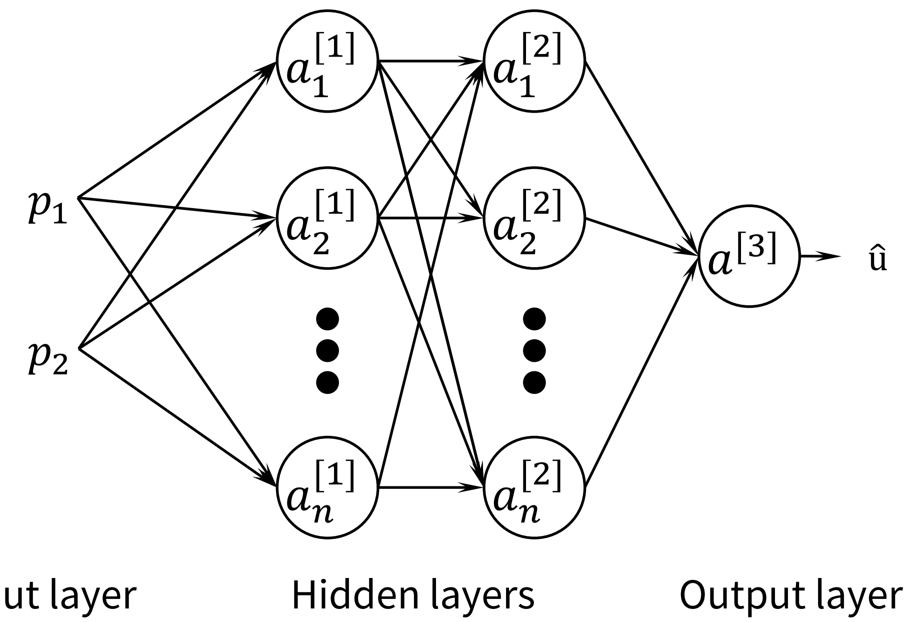
Direct correlation with material properties

Success in many other fields

Artificial neural networks

- ANNs is one of the most popular machine learning techniques
  - Convolutional neural network (CNN): image classification
  - Recurrent neural network (RNN): natural language processing

Traditional artificial neural networks



Output: $\hat{u} = f_{\boldsymbol{\theta}}(\mathbf{p})$

Cost function: $J(\boldsymbol{\theta}) = \dfrac{1}{N}\sum_{i=1}^{N}[f(\mathbf{p}_i) - f_{\boldsymbol{\theta}}(\mathbf{p}_i)]^2$

Parameters update: $\boldsymbol{\theta}_{n+1} = \boldsymbol{\theta}_n - \eta\nabla_{\theta}J(\boldsymbol{\theta}_n)$

- No physics involved in ANNs
- Requires a lot of training data to learn behavior
- Limited performance in the regime where training data is scarce

Need for an alternative approach

Physics-informed neural networks

- Physics-informed neural network (PINN): Physics-based equation or governing equation is provided to ANNs as a prior knowledge*

- Governing equations are typically partial differential equations (PDEs)
  - Heat equation, Diffusion equation, Wave equation, Etc.

- PINN can be used to solve for
  - Forward problem: the process of determining the solution
  - <u>Inverse problem</u>: the process of determining parameters or model

- How to implement physics-based equations?

$$J(\boldsymbol{\theta}) = \underbrace{\frac{\lambda_1}{N}\sum_{i=1}^{N}[f(\mathbf{p}_i) - f_{\boldsymbol{\theta}}(\mathbf{p}_i)]^2}_{\text{Data fit}} + \underbrace{\frac{\lambda_2}{N}\sum_{i=1}^{N}[\mathcal{R}(\mathbf{p}_i)]^2}_{\text{Physics-based regularization}}$$

E.g.: wave equation

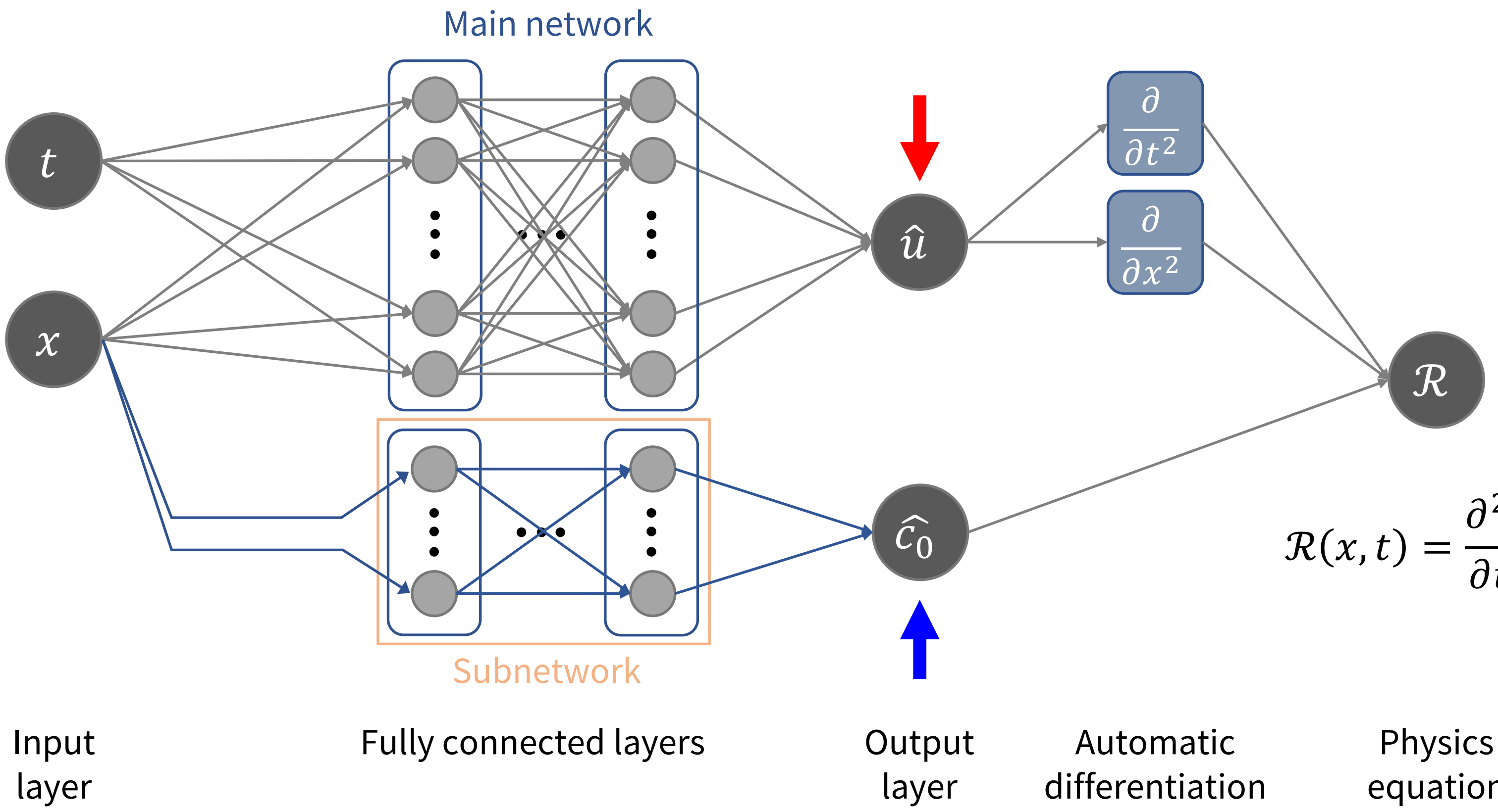
$$\frac{\partial^2 u}{\partial t^2} - c_0\frac{\partial^2 u}{\partial x^2} = 0$$

$$\mathcal{R}(\mathbf{p}_i) = \frac{\partial^2}{\partial t^2} f_{\boldsymbol{\theta}}(\mathbf{p}_i) - c_0\frac{\partial^2}{\partial x^2} f_{\boldsymbol{\theta}}(\mathbf{p}_i)$$

*Raissi, Maziar, Paris Perdikaris, and George E. Karniadakis. "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations." *Journal of Computational physics* 378 (2019): 686-707.

PINN architecture: 1D case

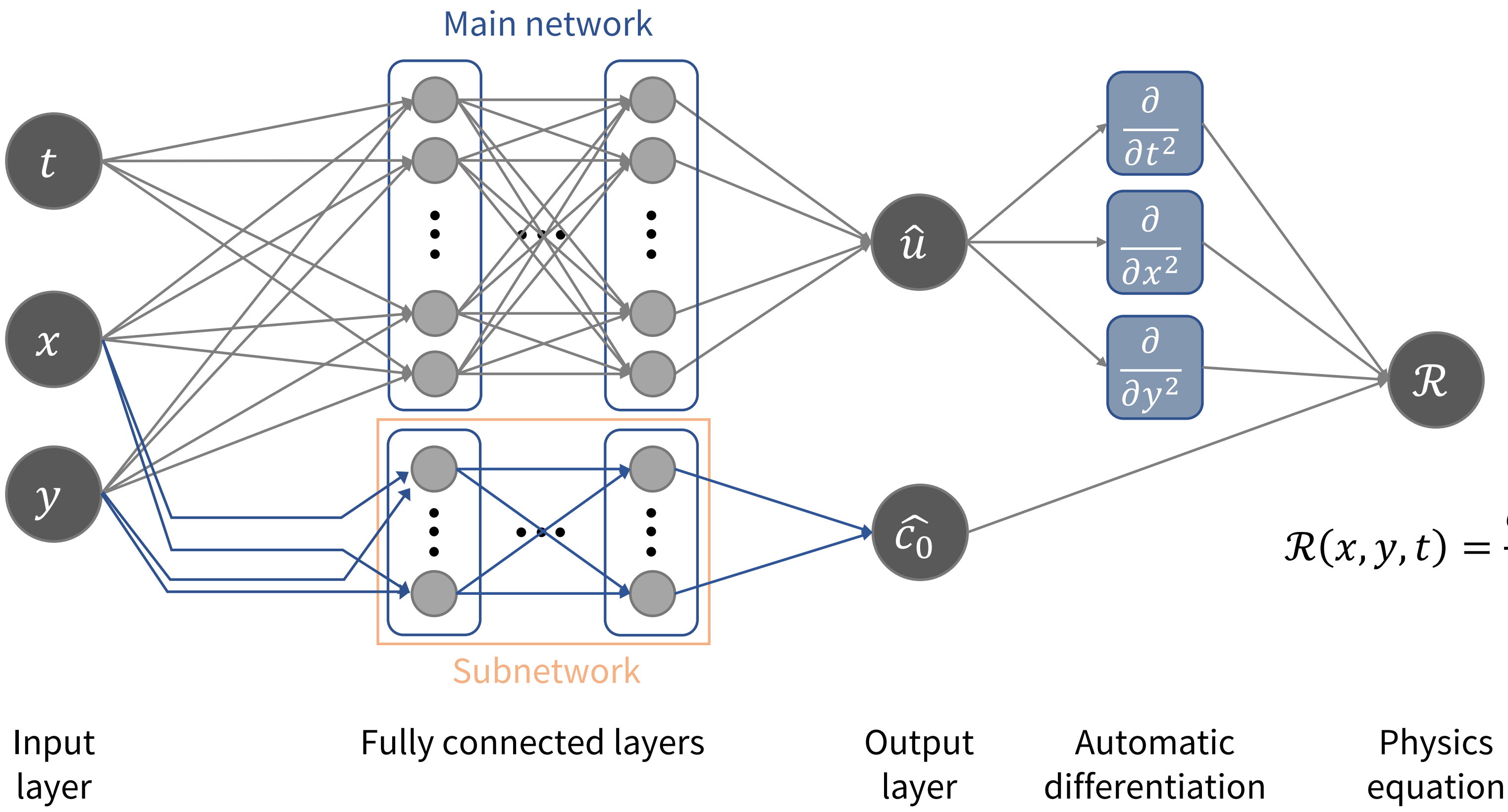
- Goal: solve inverse problems of the wave equation using ultrasonic wave data



$$\mathcal{R}(x,t) = \frac{\partial^2 \hat{u}}{\partial t^2} - \hat{c}_0^2(x)\left[\frac{\partial^2 \hat{u}}{\partial x^2}\right]$$

PINN architecture: 2D case

- Goal: solve inverse problems of the wave equation using ultrasonic wave data



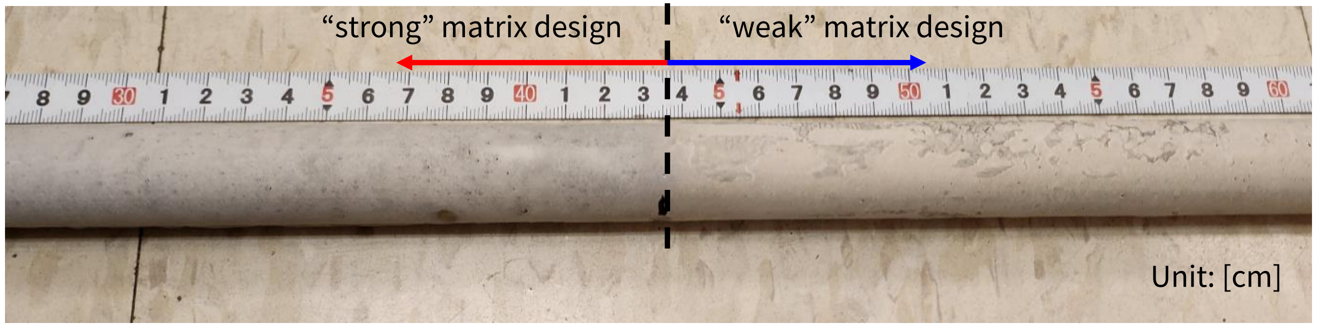
$$\mathcal{R}(x,y,t) = \frac{\partial^2 \hat{u}}{\partial t^2} - \hat{c}_0^2(x,y)\left[\frac{\partial^2 \hat{u}}{\partial x^2} + \frac{\partial^2 \hat{u}}{\partial y^2}\right]$$

Experimental setup

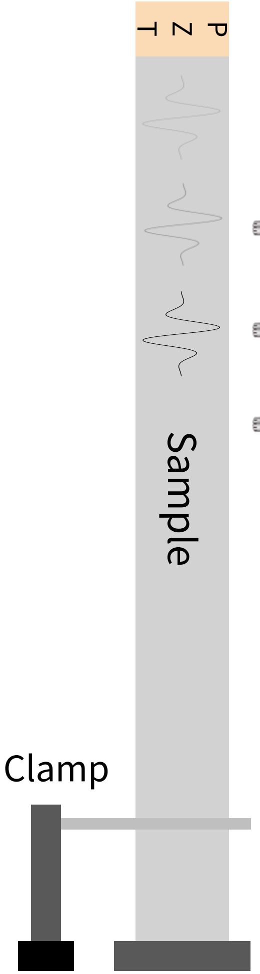
Long rod-shaped samples

- Two materials: steel and mortar
- Steel:
    - D-10 mm, L-1700 mm
- Mortar:
    - D-25.4 mm, L-1470 mm
    - “strong”=w/c: 0.5, “weak”=w/c: 0.6
    - c:s = 1:3

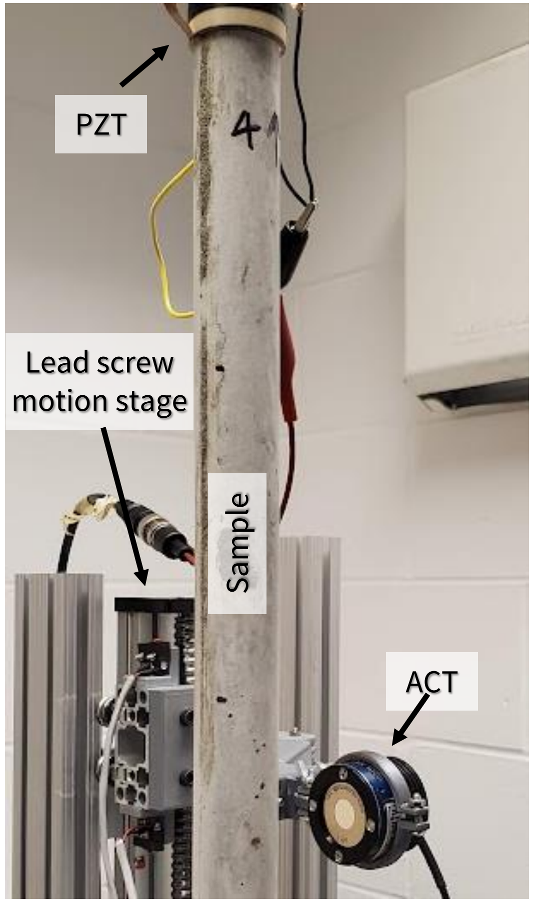
- Excitation: PZT disc, 145 and 75 kHz
- Receiver: broadband air-coupled transducer



(a) *Only a minor color difference between the two section is observed*



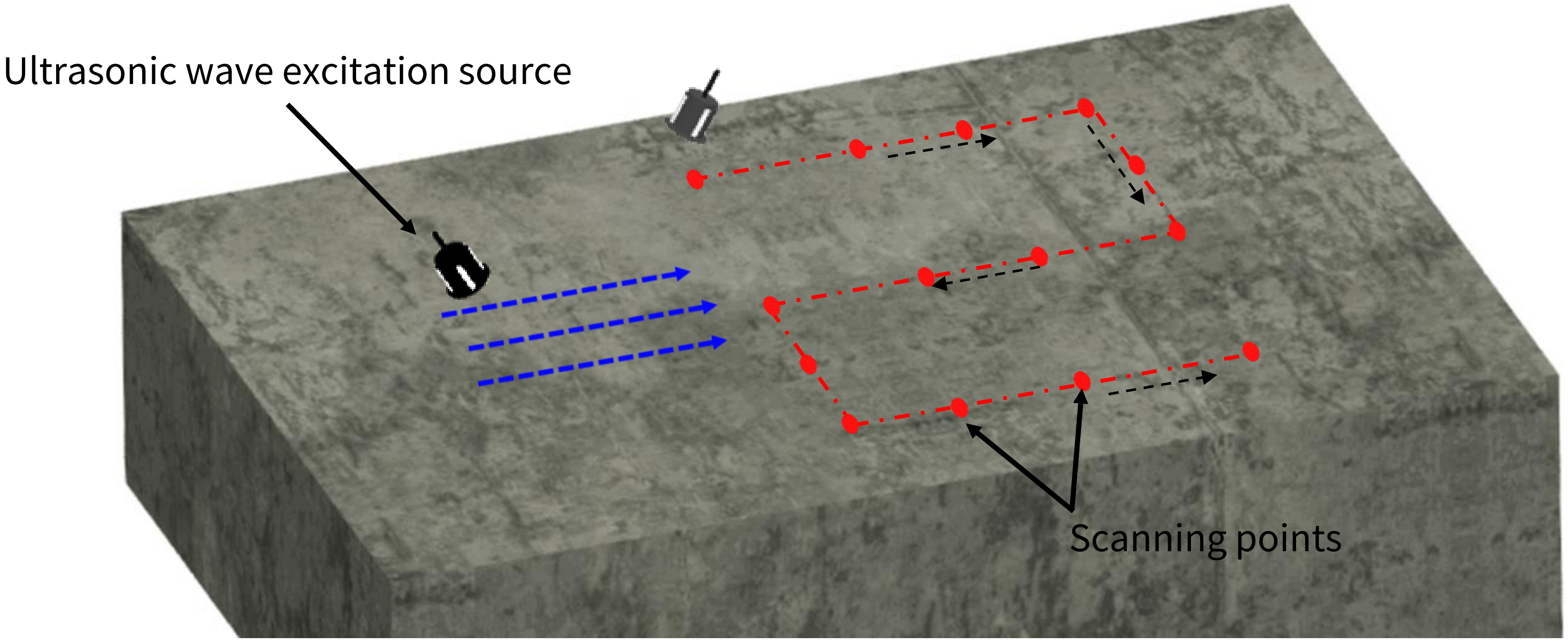
(b) *Testing scheme*



(c) *Detailed view of the measurement system*

Numerical simulations

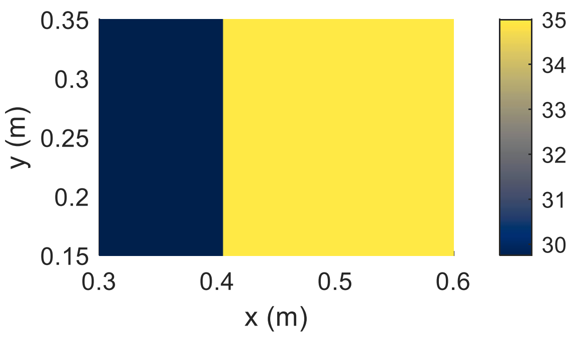
- Additional data sets were collected from numerical simulations
- The simulation considered a concrete slab or bridge deck.



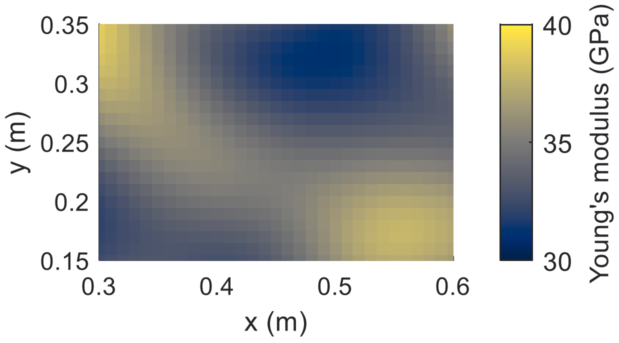
Numerical simulations

Young’s modulus map

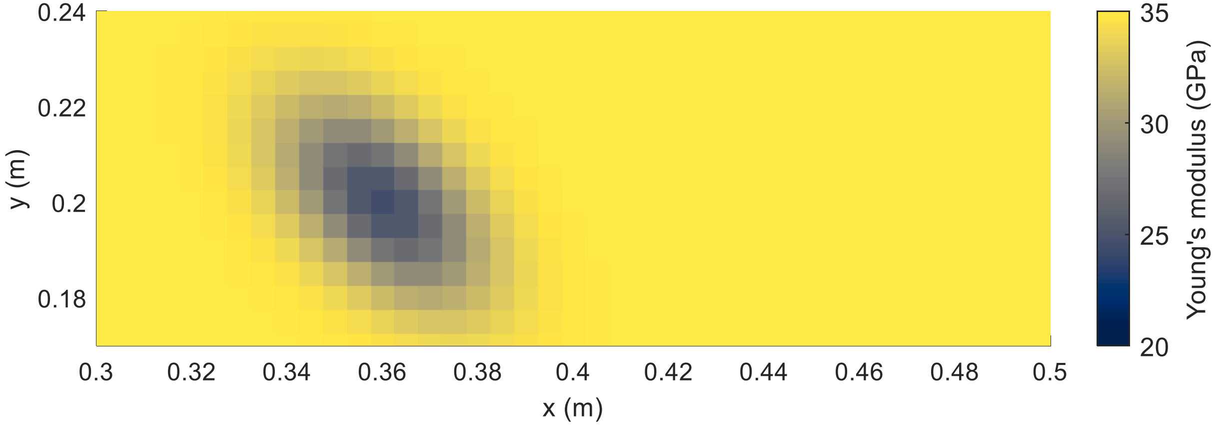
Case 1



Case 2

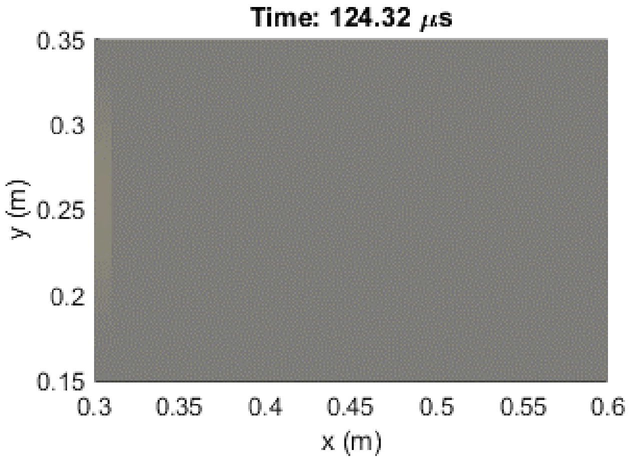


Case 3

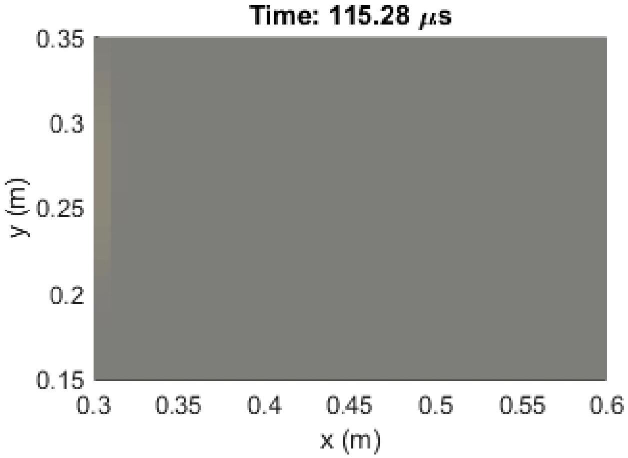


Wave propagation simulation data

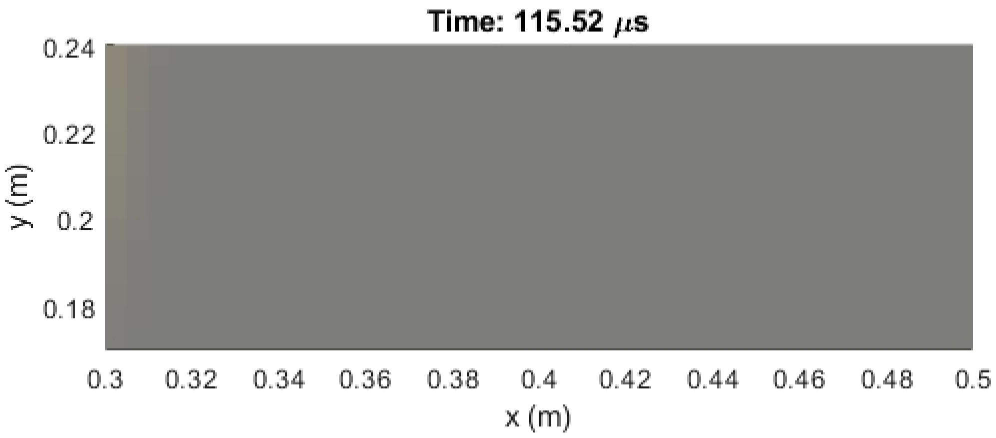
Case 1



Case 2



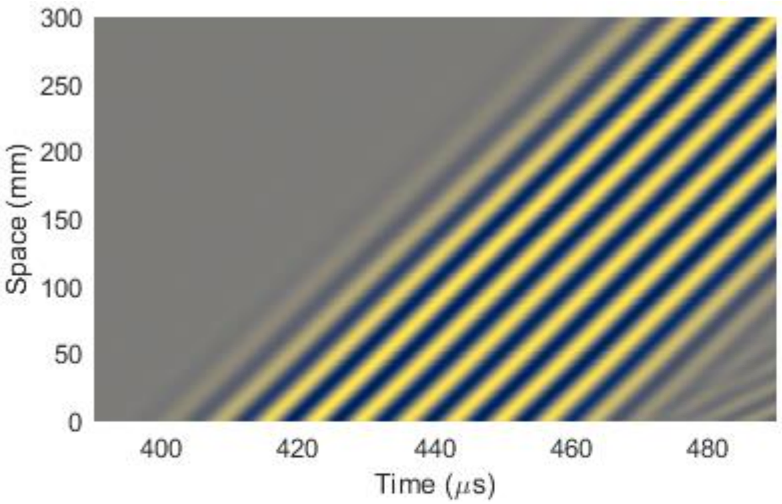
Case 3



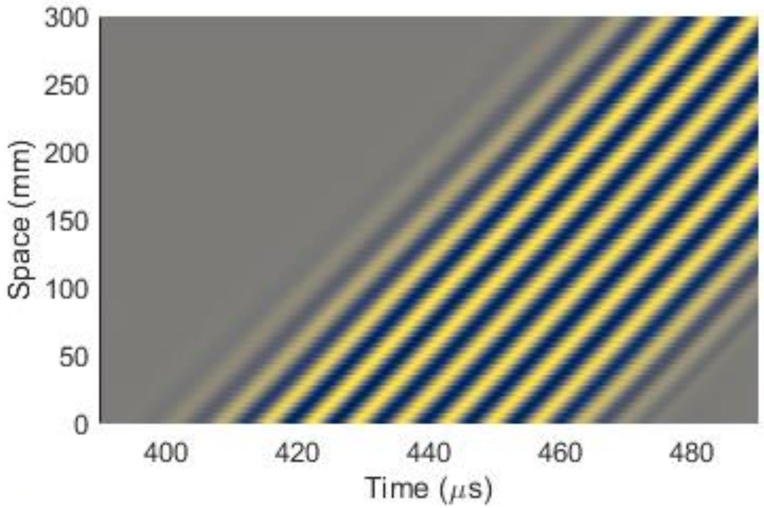
PINN results for experimental data

Steel

Measurement data



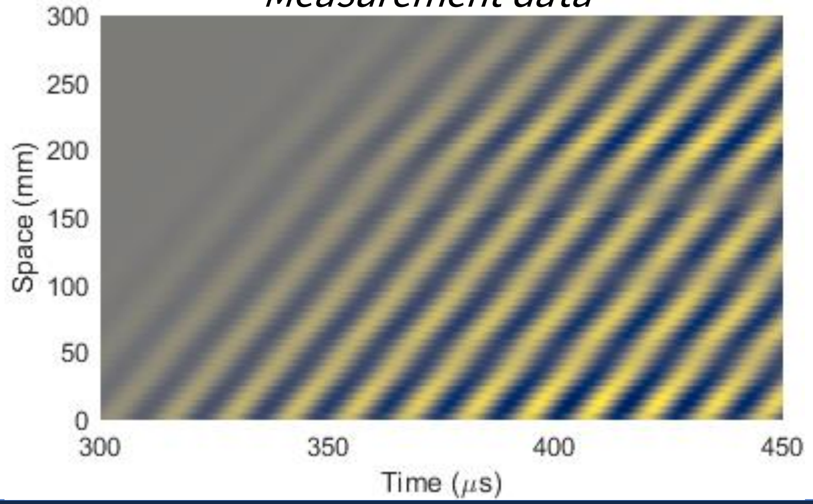
PINN prediction results



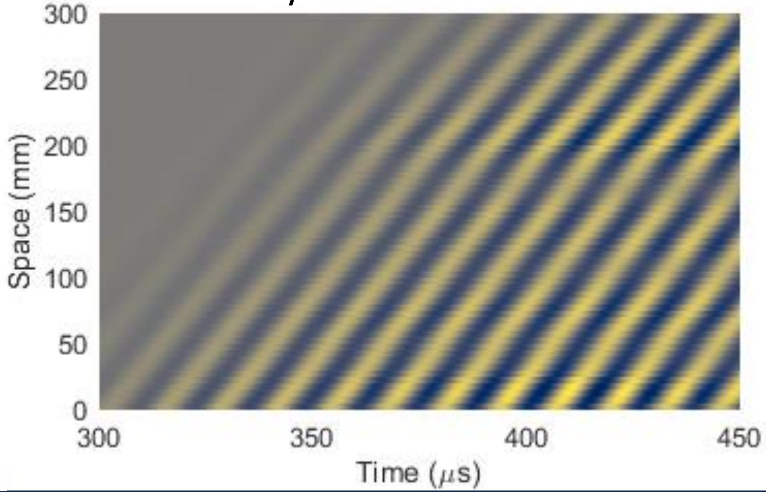
$$\frac{\partial^2 u}{\partial t^2} - \boxed{c_0}\frac{\partial^2 u}{\partial x^2} = 0$$

Mortar

Measurement data

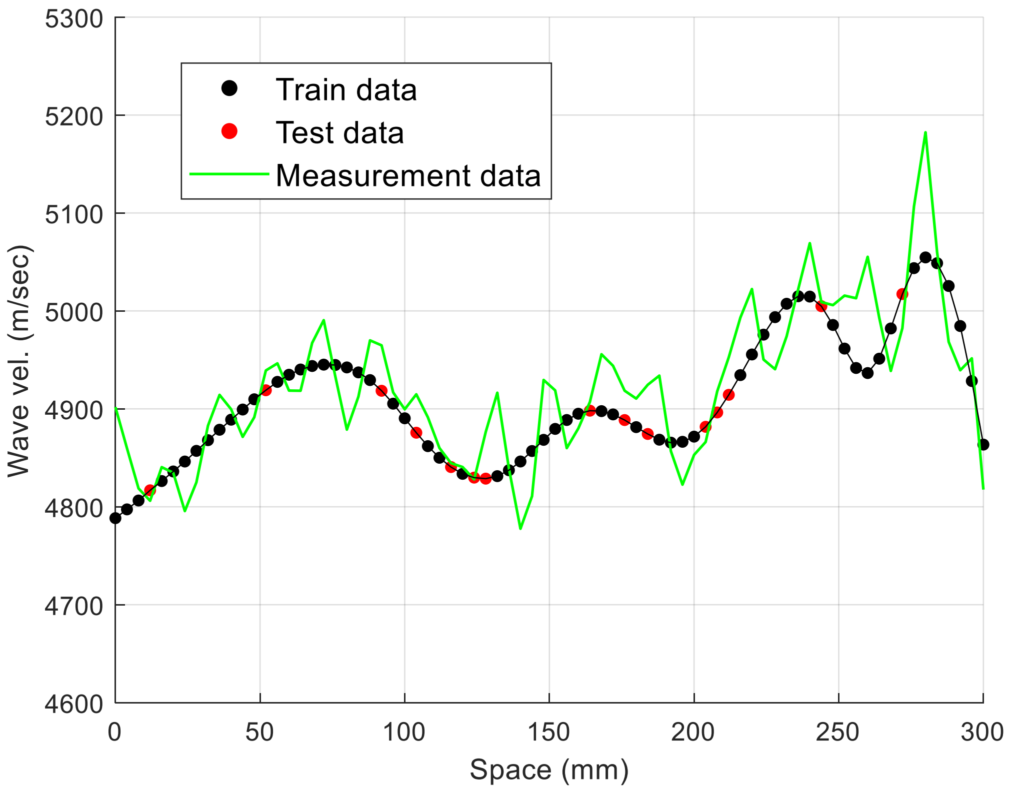


PINN prediction results



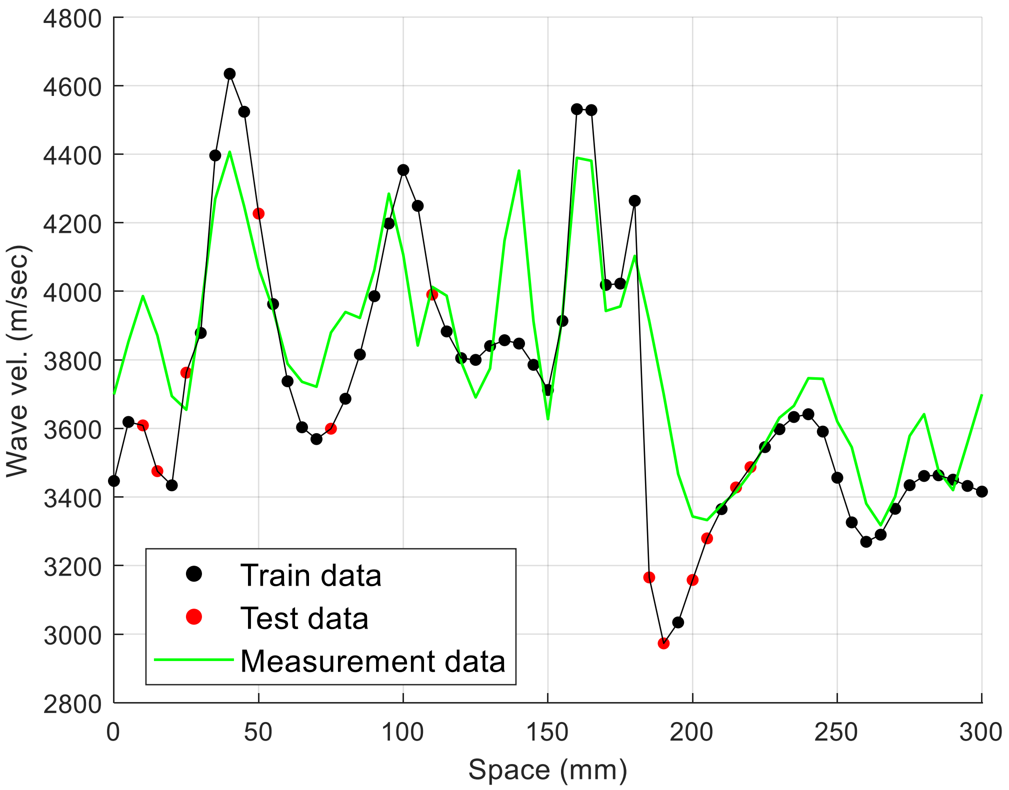
PINN results for experimental data

Steel



Relative error: 0.15 %

Mortar

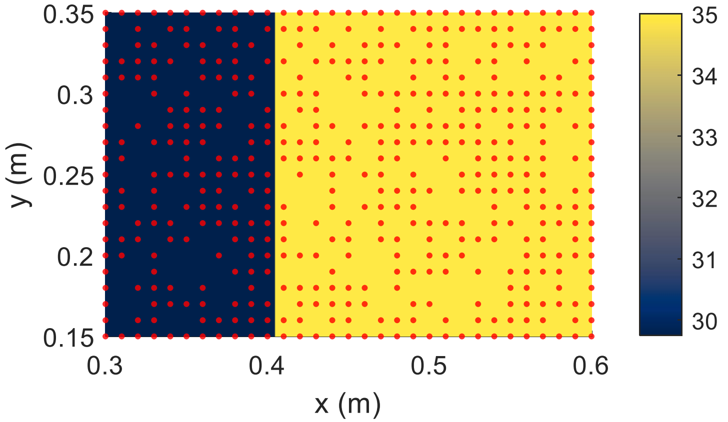


Relative error: 1 % (“strong”), 4 % (“weak”)

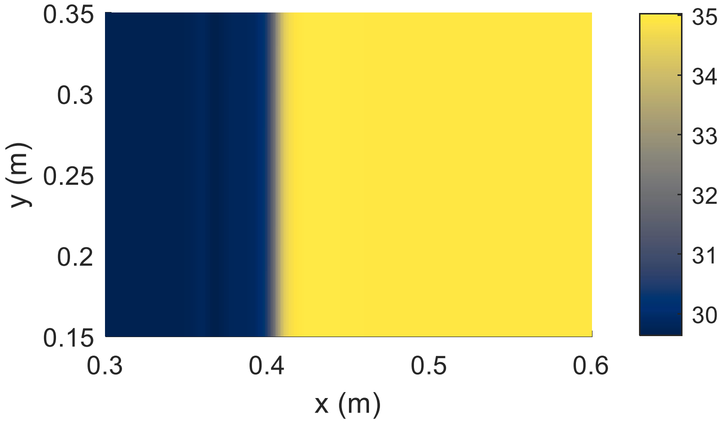
PINN results for simulated data

Case 1

True map



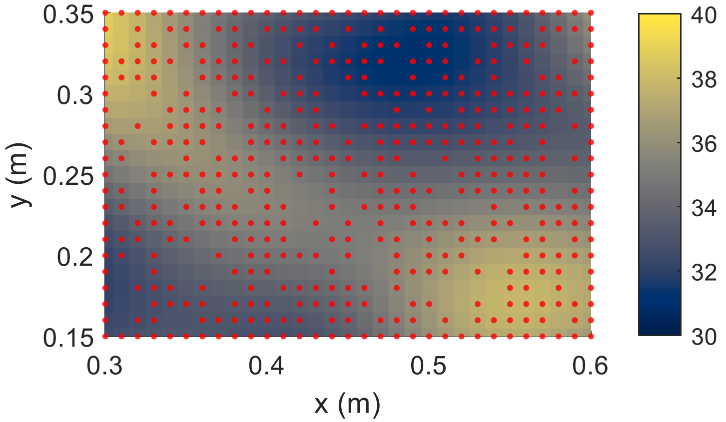
PINN prediction



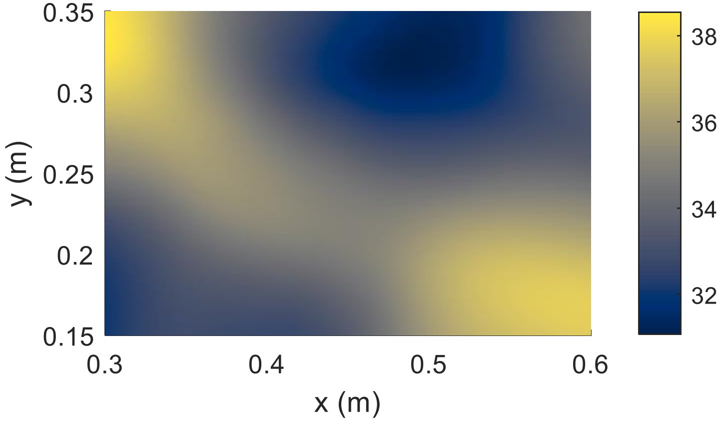
Relative L2 norm error: 0.64 %

Case 2

True map



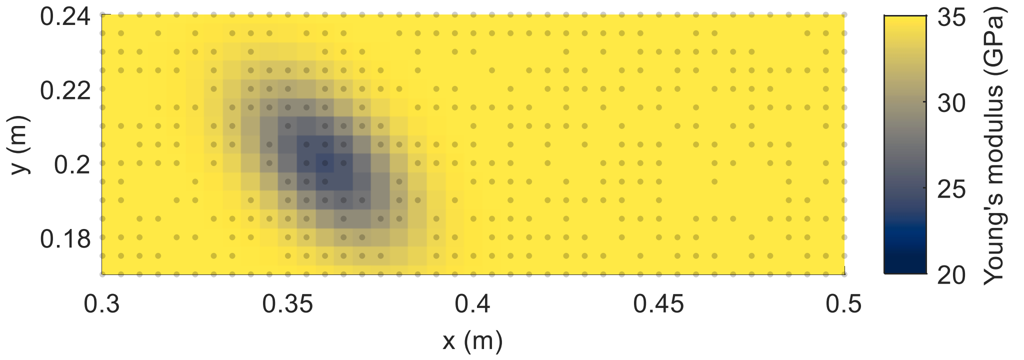
PINN prediction



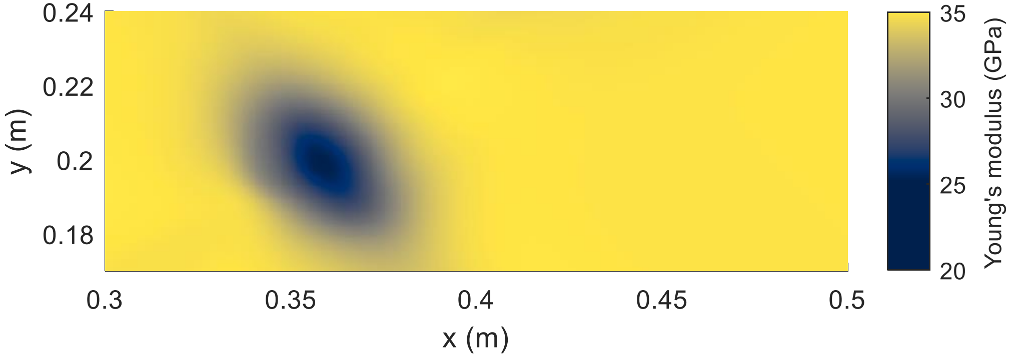
Relative L2 norm error: 0.45 %

Case 3

True map



PINN prediction



Relative L2 norm error: 0.56 %

Conclusion

- Method for characterizing concrete mechanical properties using ultrasonic propagation data and physics-informed neural network (PINN) was investigated.

- Material wave velocity profile as a function of space was predicted using experimental data from steel and mortar samples

- Simulated ultrasonic data in concrete slabs with defects were created through numerical simulations, and the damage zones were detected by predicting spatial-dependent Young's modulus.

- PINN shows great potential for characterizing inhomogeneous material properties as a function of space, with potential applications in *in situ* assessment of concrete structures.

Thank you

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