Convolutional neural network-based seismic response prediction method using spectral acceleration of earthquakes and conditional vector of structural property

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2024

Introduction

Significance:

Enhancement of seismic response prediction (SRP) by combining spectral acceleration (Sa) and structural properties in a convolutional neural network (CNN)

Area of expertise:

- Seismic Risk Assessment (SRA)
- Seismic Response Prediction
- Spectral Acceleration Analysis (SAA)
- CNN based Approaches

Problem statement

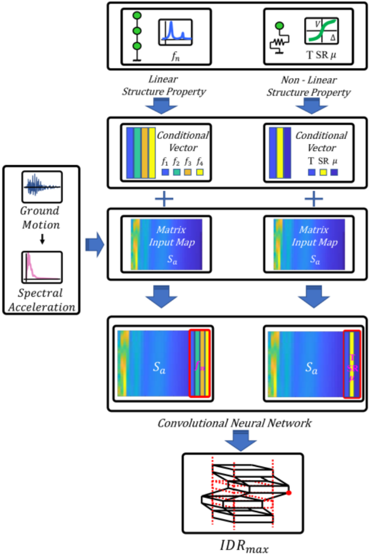
The problem:

- Limited prediction accuracy
- Poor handling of nonlinear structural behaviors
- Fragility across diverse structures, seismic events

Goals:

- Accuracy improvement
- Seismic and structural data integration
- Better generalization

- Large datasets of structures and seismic events
- Inputs:
  1. Sa as seismic data
  2. Structural properties
- Output: Maximum inter-story drift ratio (IDR_{max})



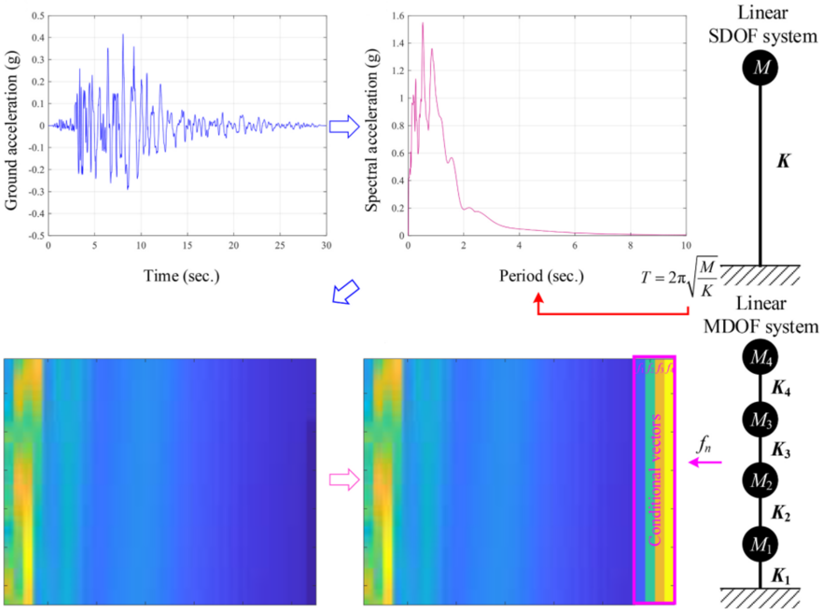
Method: Linear structure prediction

- Inputs:
  1. Sa as a matrix covering a range of periods
  2. Natural frequencies as conditional vectors

- Output: Predicted IDR_{max}

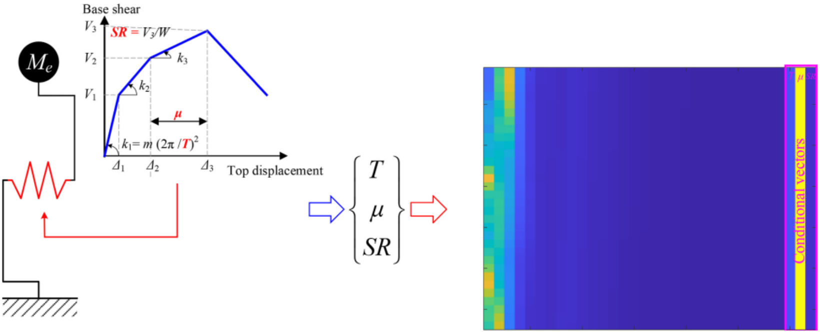
- Models:
  1. WO: Without conditional vectors
  2. WC: With conditional vectors

Method: Linear structure prediction



Method: Nonlinear structure prediction

- Inputs:
  1. Sa as a matrix covering a range of periods
  2. Nonlinear structural properties (T-μ-SR) transformed into conditional vectors
- Output: Predicted $\mathrm{IDR}_{\mathrm{max}}$
- Models:
  1. NW: Without conditional vectors
  2. NWC: With conditional vectors



Method: CNN architecture

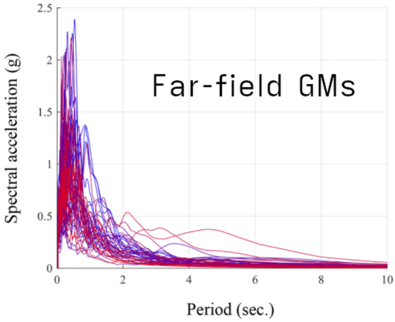
- Activation: Sigmoid function for output values
- Optimization: Gradient descent method with loss function
- Training setup:
  - Batch size: 100
  - Epochs: 1000

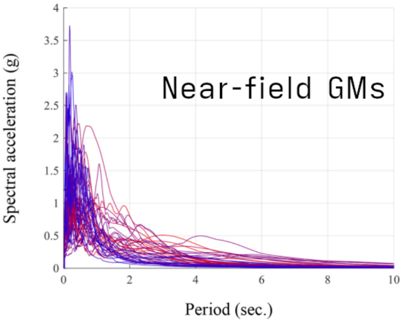
Layer	Size/ Depth	Operator	Size/ Stride
Input layer	32×32	Kernel 1	$15 \times 15/\ 1$
Convolutional layer 1	$18 \times 18/\ 10$	Subsampling 1	$2 \times 2/\ 2$
Pooling layer 1	$9 \times 9/\ 10$	Kernel 2	$7 \times 7/\ 1$
Convolutional layer 2	$3 \times 3/\ 20$	Subsampling 2	$1 \times 1/\ 1$
Pooling layer 2	$3 \times 3/\ 20$		
FC layer	180×1		
Output layer	1×1		

Experiments

- 100 earthquakes
- PGA: 0.21g – 1.43g
- Training set: 70%
- Testing set: 30%

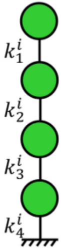
- Experiments:
  - Linear structures
  - Nonlinear structures



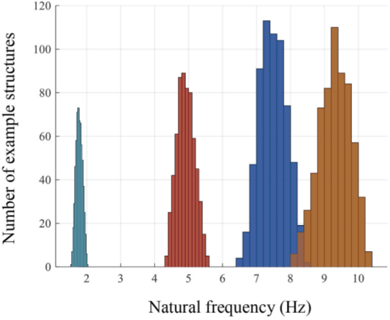


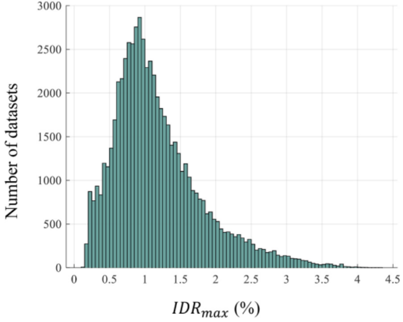
Experiment: Linear structures

- 625 structures
- 62'500 scenarios



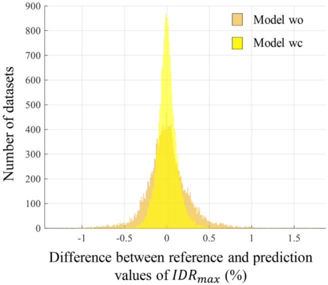
$$k_j^i = k_j^0 \, r_j^i$$
$$r_j = 0.6 \; to \; 1.0$$
$$i = 1 \; to \; n \quad and \quad j = 1 \; to \; m$$
$$n = 625$$
$$m = 4$$

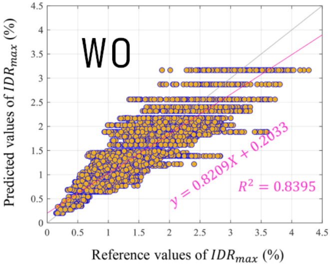


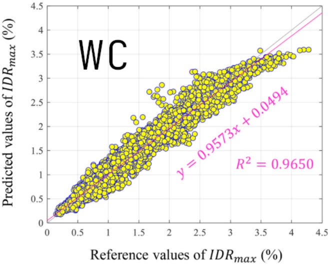


Results and discussion: Linear structures

- Model:
  - WO:
    - RMSE: 0.2541
    - R^2: 0.8395
  - WC:
    - RMSE: 0.1187
    - R^2: 0.9650

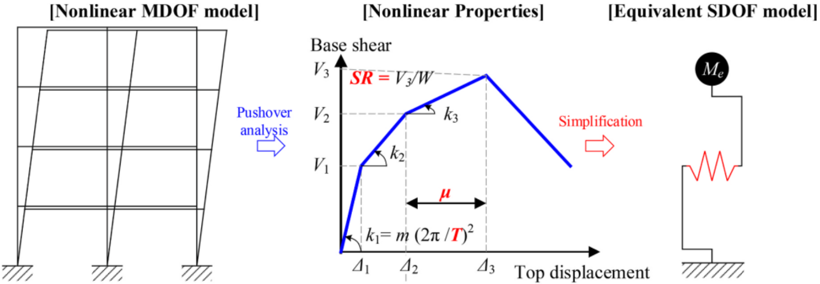






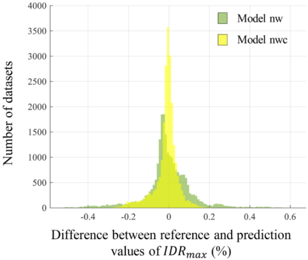
Experiment: Nonlinear structures

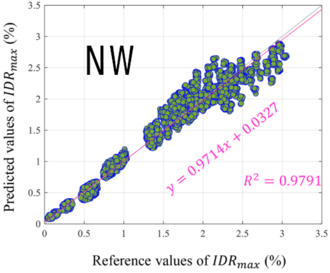
- 768 structures
- 76'800 scenarios

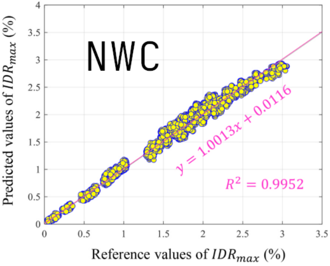


Results and discussion: Nonlinear structures

- Model:
  - NW:
    - RMSE: 0.1194
    - R^2: 0.9791
  - NWC:
    - RMSE: 0.0597
    - R^2: 0.9952







Conclusion

- Model performance
  - Linear models:
    - WO: poor accuracy
    - WC: high accuracy
  - Nonlinear models (NW, NWC): exceptional accuracy
- Conditional data impact: ∼2x improvement (RMSE)
- Future work: Seismic loss functions for structural damage and financial cost estimation

Thank you for your attention!