Presentation notes

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1 Introduction

This study addresses the need for accurate seismic response prediction by integrating seismic information and structural properties using convolutional neural networks (CNNs). Unlike traditional methods, which often rely on limited data or scalar seismic parameters, this approach leverages big data from multiple structures and earthquakes. Spectral acceleration (Sa) and structural characteristics, including nonlinear behaviors, are transformed into input maps for CNNs, enabling precise predictions of seismic responses like maximum inter-story drift ratio (IDRmax). This method significantly enhances prediction accuracy and provides valuable insights for seismic risk assessment and earthquake engineering.

2 Problem statement

Problem:

- Traditional seismic response prediction methods often rely on limited scalar parameters, such as spectral acceleration (Sa) at specific periods, reducing prediction accuracy.
- Nonlinear structural behaviors, crucial for accurate seismic response modeling, are often not effectively captured in existing approaches.

- Existing models may lack robustness when applied to diverse structures and seismic events due to insufficient integration of structural properties and seismic information.
- The high computational cost and time associated with traditional nonlinear time-history analyses hinder practical large-scale applications.

The Goal:

- Develop a CNN-based method to predict seismic responses with higher accuracy by integrating seismic and structural characteristics.
- Represent seismic information (Sa) and structural properties in a comprehensive input map suitable for CNN processing.
- Train models using large datasets generated from diverse structures and seismic waves to improve generalizability.
- Provide an efficient alternative to computationally expensive traditional methods while maintaining reliability.

3 Method

3.1 Seismic Response Prediction Using CNN

This study focuses on predicting the seismic response of buildings using CNNs, a machine learning technique. The CNN takes seismic information, specifically spectral acceleration (Sa), and structural properties like frequency characteristics as inputs. The output is the maximum inter-story drift ratio (IDRmax), which indicates structural response under seismic forces. To train the model, we used large datasets of simulated seismic data and structural characteristics. This approach helps predict responses to future earthquakes more accurately, aiding in structural safety assessments.

3.2 Linear Structure Prediction Method

For linear structures, the method inputs spectral acceleration, represented as a matrix covering various periods, and structural natural frequencies. These frequencies are transformed into conditional vectors for better feature extraction. The output is the predicted maximum drift ratio, IDR_{max}. Two models are used: Model WC includes structural properties, while Model WO does not. This allows for performance comparisons to evaluate the impact of including structural data. This method enhances prediction accuracy for buildings with linear response characteristics under seismic events.

3.3 Nonlinear Structure Prediction Method

For nonlinear structures, the method uses spectral acceleration in matrix form, similar to the linear approach, but also includes nonlinear structural properties. These properties, represented as T-μ-SR values, reflect the structure's hysteretic behavior under seismic loads. The inputs are transformed into conditional vectors for use in the CNN. The model, called NWC, predicts IDRmax for nonlinear structures. By incorporating parameters like ductility and strength ratios, this approach models the complex behavior of real-world buildings under earthquake conditions.

3.4 CNN Architecture

The CNN architecture used in this study is relatively shallow, with two convolutional layers followed by pooling layers and a fully connected layer leading to the output. The sigmoid activation function produces the final prediction values. Training involved optimizing a loss function using gradient descent. The model was trained with a batch size of 100 over 1,000 epochs, enabling the extraction of meaningful patterns from the data. This efficient architecture balances simplicity and accuracy, making it ideal for seismic response prediction tasks.

4 Conclusion

- Seismic Response Prediction:
  - Models using both seismic info and structural properties outperformed those using only seismic data.

- Structural properties are essential, especially for nonlinear structures, where excluding them hindered CNN training.

- Effectiveness of Conditional Vectors:
  - Structural properties in conditional vector form improved prediction accuracy for both linear and nonlinear structures.
  - Conditional vectors were particularly beneficial for nonlinear structures with high nonlinearity.

- Impact of Seismic Intensity Measures:
  - Seismic intensity measures in scalar form showed little improvement.
  - Using them as conditional vectors significantly enhanced prediction accuracy.

- Future Work: Develop seismic loss functions for rapid response predictions to assess structural damage and financial losses, aiding seismic retrofitting decisions.