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Preliminary study for CNN-based Damage prediction of SDOF Structure

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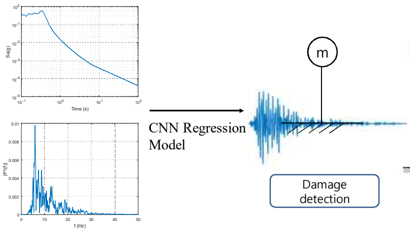
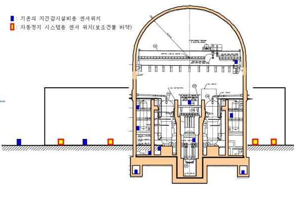
Introduction

- Frequency of Earthquake in Korea is gradually increased recently.
- Recently, studies using artificial neural networks to predict future responses based on earthquake observation results of structure are being conducted.
- Convolution Neural Network (CNN), one of deep learning algorithms, was used to predict damage by considering the Fast Fourie Transform (FFT) of structures as an image data.
- As a preliminary study to evaluate the state of the structure through CNN, the stiffness of single degree of freedom (SDOF) system was considered.
- The change of stiffness of the structure was precited through several learning cases.



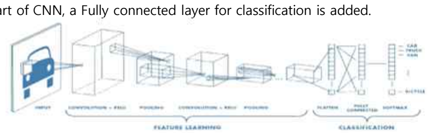
Nuclear Power Plant Seismic Monitoring System



Nuclear Power Plant Seismic Monitoring System

Convolution Neural Network

- A neural network model that is mainly used for image or video data processing in deep learning and includes a pre-processing task as called convolution.
- CNN receives images as raw inputs and builds up a layer of features while maintaining spatial/local information.
- CNN can be divided into a part of Extracting features and a part of Classifying as shown in the figure below.
  - The Feature extraction area is composed of several layers of a convolution layer and a pooling layer
    - Convolution layer is an essential element that reflects the activation function after applying a filter to the input data.
  - In the last part of CNN, a Fully connected layer for classification is added.



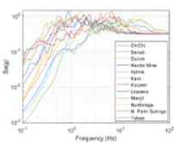
CNN Model structure & Layer

NGA-WEST Database

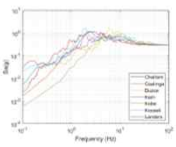
- Lack of domestic earthquake record data
  - From NGA-WEST2 Database, training data sets are prepared.
- Classification of earthquakes according to A/V ratio
  - A/V ratio is one of parameters representing dynamic characteristics of ground motion.
  - A/V ratio can be classified into 3 parts
    - Low: (avr1<0.8) & (avr2<0.8) (unit: g/m/s)
    - Mid: (0.8≤avr1 ≤1.2) & (0.8 ≤avr2 ≤1.2)
    - High: (avr1>1.2) & (avr2>1.2)
- Considerations for deriving earthquake data
  - Data recording for 3-directions (H1, H2, and V)
  - PGA of H1 or H2 ≥ 0.1g
  - Shear wave velocity of 30 m ≥ 300m/s
    → The nonlinear behavior of the ground (Stiffness ↓, Damping ↑) was not significant at this site
- In each set, one observed record is selected.
  - When 'Low' is recorded in two observation networks of Chi-Chi earthquake, the record with a smaller A/V ratio is selected.
  - When 'Low', 'Mid', 'High' were recorded in each of the three observation networks of Chi-Chi earthquake, each recorded was used.

Table.

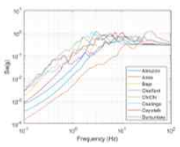
Earthquake	Magnitude	$V_{s,30}$(m/s)	Max. Acc. (g)	Max. Vel. (g)	A/V ratio (g/m/s)
Low					
Chi-Chi	7.62	378.75	0.2995	0.4512	0.6638
Denali	7.9	329.4	0.3326	1.1566	0.2876
Duzce	7.14	529.18	0.1072	0.1581	0.6781
Westmorland	5.9	348.69	0.2321	0.5555	0.4178
Mid					
Coalinga	6.36	307.59	0.1932 0.1239	0.1886 0.1301	1.0242 0.9031
Duzce	7.14	481	0.1312 0.1010	0.1212 0.1119	1.0824 0.9031
ManJil	4.37	302.64	0.1840 0.1307	0.1549 0.1095	1.1879 1.1939
High					
Anza	4.92	70	0.1506	0.0172	8.777
Chi-Chi	7.62	492.26	0.6394	0.3732	1.7135
Coalinga	6.36	410.4	0.1431	0.0859	1.6657



A/V Low



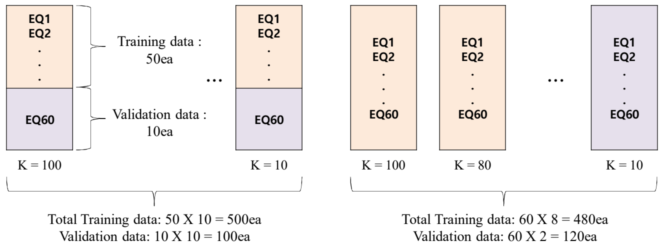
A/V Mid



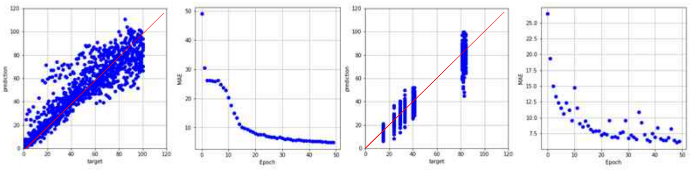
A/V High

CNN Model of damage prediction

- A total of 6,000 datasets are prepared by obtaining structural responses according to the earthquake data (60ea).
  → According to the change of stiffness of structure, FFT data was obtained.
  - The frequency domain structure responses is utilized as an image for training.
- By dividing the training dataset into two types, CNN model is constructed and the results were compared.
  → Case 1: various input seismic loads with constant stiffness
  → Case 2: change of stiffness with constant earthquake



- The results using the CNN model are as follows.
  → Prediction with CNN regression model / Training Loss (Mean Absolute Error)



Case 1 Case 2

Summary

- Damage detection of SDOF
  - Construct an image data of structural responses into frequency domain (FFT)
  - Build a dataset by changing the stiffness of the structure according to the input seismic load
  - Damage detection of SDOF according to the learning cases
  - Confirm the trends of results despite of the lack of dataset
- NGA-WEST2 Database
  - Use the dataset of NGA-WETS2 DATABASE due to the lack of the domestic earthquake records
  - Classify the earthquakes according to the A/V ratio → dynamic parameter of ground motion
  - Use the classified earthquake records for further research

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