A machine-learning approach toward assessing severity of earthquake induced damage

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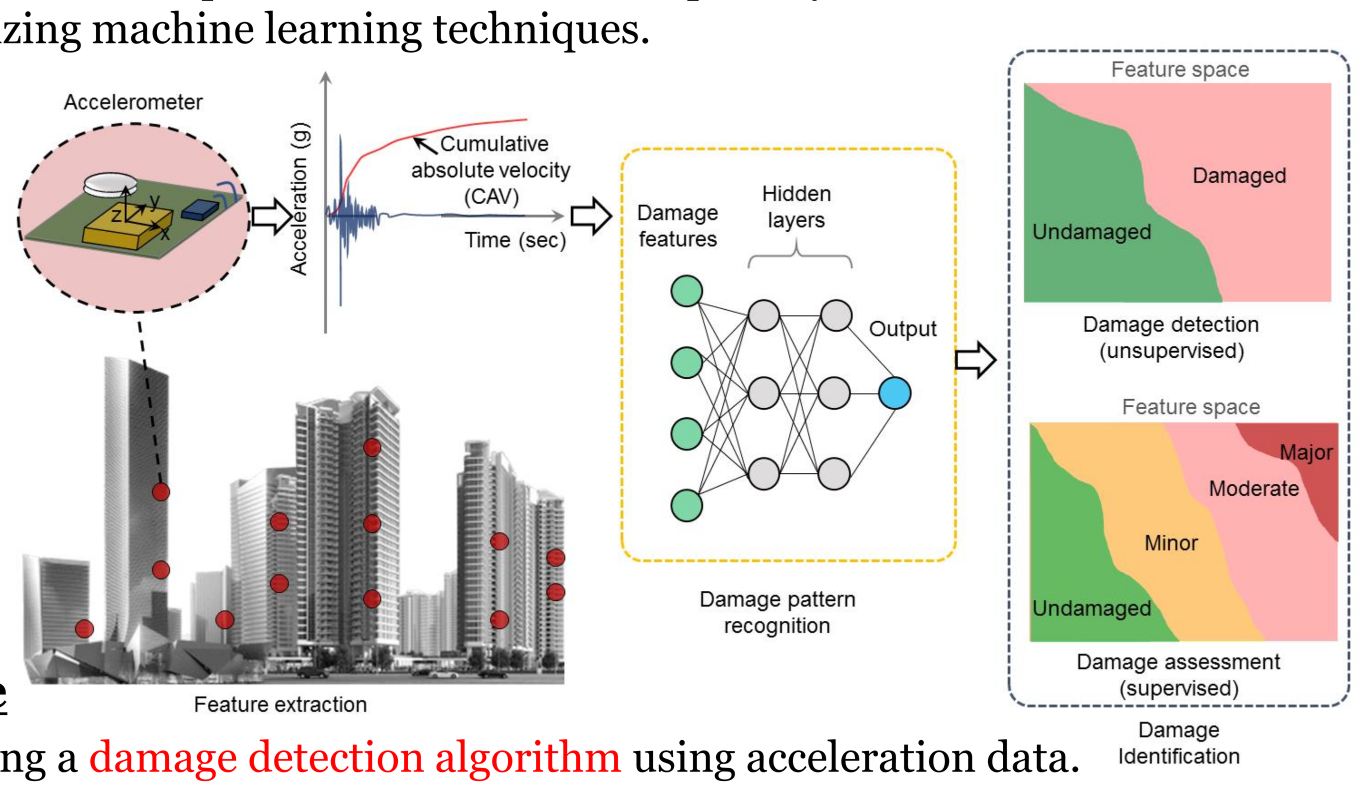
INTRODUCTION

Structural health monitoring (SHM) is necessary to monitor the structural integrity and assess deterioration for safe and continuous operation of these infrastructures. Advances in remote sensing, computing technologies, and data science in the past few years paved the way to develop SHM techniques that can assess and quantify the condition of structures in near-real time utilizing machine learning techniques.



Objective

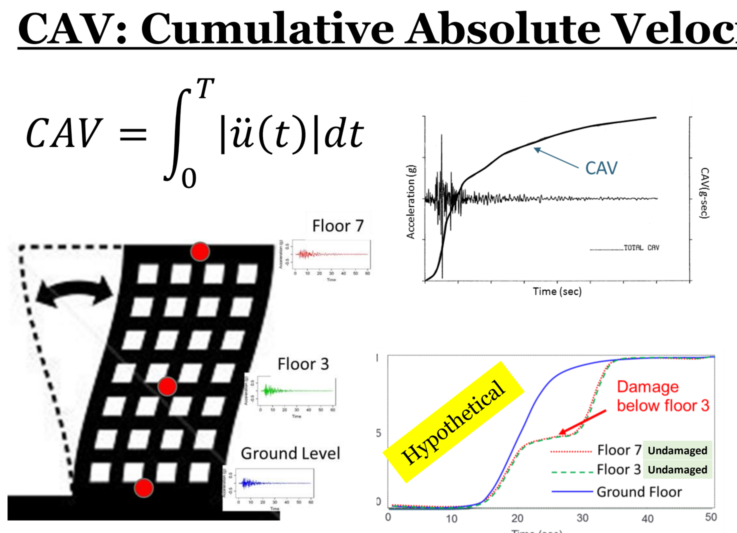
1. Developing a damage detection algorithm using acceleration data.
2. Utilizing the cumulative absolute velocity (CAV) of sensed data as a damage feature.
3. Applying machine learning tools to identify existence, location and extent of the damage.

RESEARCH MOTIVATION & BACKGROUND

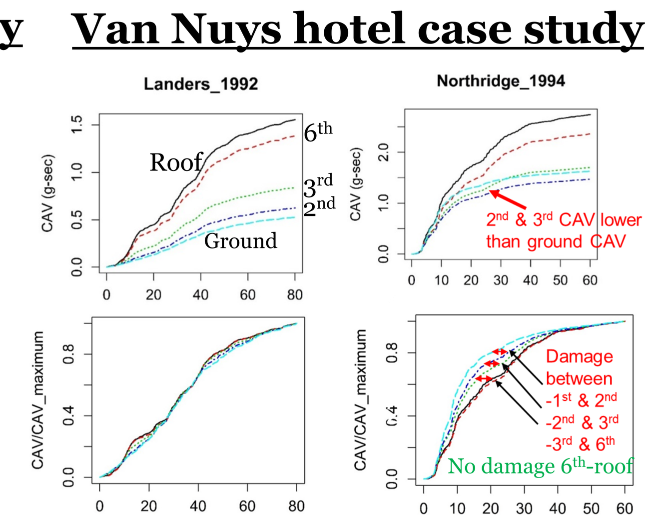
Motivation of this project stems from a previous study where CAV analysis successfully detected and located damage.

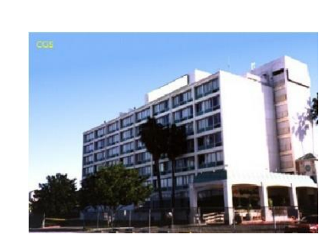
CAV: Cumulative Absolute Velocity

$$CAV = \int_0^T |\ddot{u}(t)|dt$$



Van Nuys hotel case study





CAV analysis successfully detects damage below 2nd, 3rd, and 6th floor.

METHODOLOGY

PROPOSED DAMAGE FEATURES

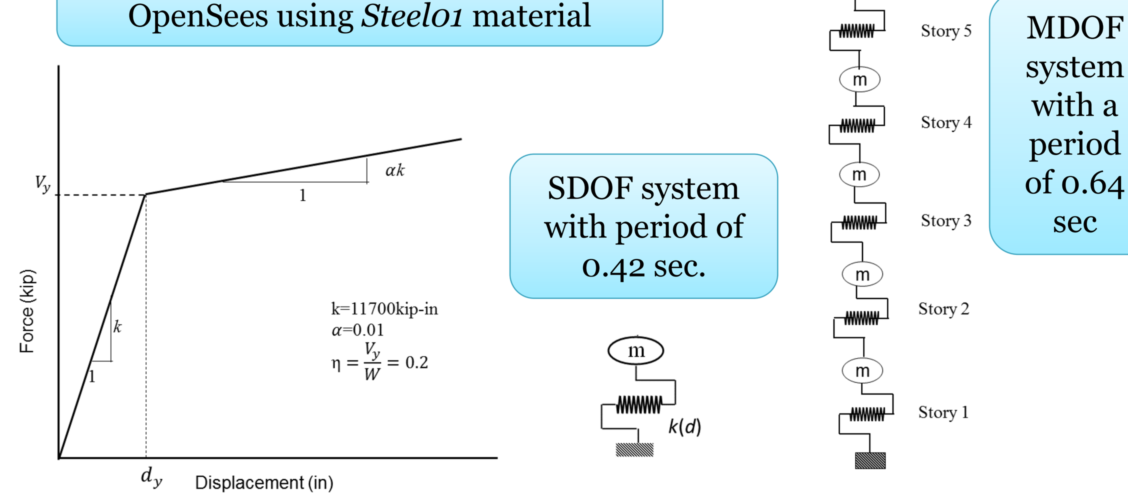
Several CAV based damage features are studied which are low dimensional and appropriate to be used in a machine learning environment with limited dataset.

Feature Symbol	Theoretical Definition	Mathematical Definition
CAV_s	CAV value at sensor	$CAV_s = CAV = \int_0^T \|\ddot{u}(t)\|dt$
R_{CAV}	Ratio of floor CAV response to Linear CAV response	$R_{CAV} = \frac{CAV_s}{CAV_l}$
S_{CAV}	Change in effective duration compared to linear model	$S_{CAV} = (D_{5-75,s} - D_{5-75,l}) \times 100\%$
Δ_{NCAV}	Total absolute deviation of NCAV (Normalized CAV with max. CAV value) compared to linear model	$\Delta_{CAV} = \text{abs}[(A_s - A_l)/A_l] \times 100\%$

OPENSEES MODELS

Two OpenSEES models are used in this study. The SDOF system is used to identify suitable features and machine learning tool. The MDOF system is utilized to determine damage assessment capability of the selected features and models for buildings.

Both models are developed in OpenSees using *Steel01* material



a. Force Displacement relationship b. SDOF system c. MDOF system

SDOF system with period of 0.42 sec.

MDOF system with a period of 0.64 sec

Acknowledgement

The authors would like to acknowledge the support from California Strong Motion Instrumentation Program (CSMIP) and the Taisei Chair in Civil Engineering, University of California, Berkeley. The authors would also like to thank Dr. Selim Günay for sharing technical information from his research.

METHODOLOGY

MACHINE LEARNING TOOLS

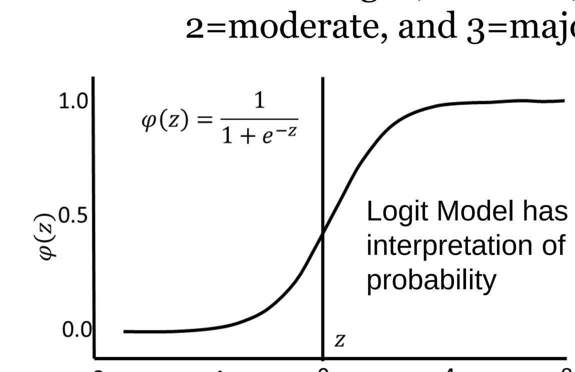
To assess damage for a given structure, three machine learning approaches are considered. All these techniques are probabilistic statistical classification models The probabilistic nature of these methods makes them better suited for this problem of damage assessment.

Logistic Regression

- A simple logistic regression (LR) is a technique applied to problems with **binary** response variable, i.e. the number of available categories are **two**.
- A **logit model** is fitted between the features and the binary response.

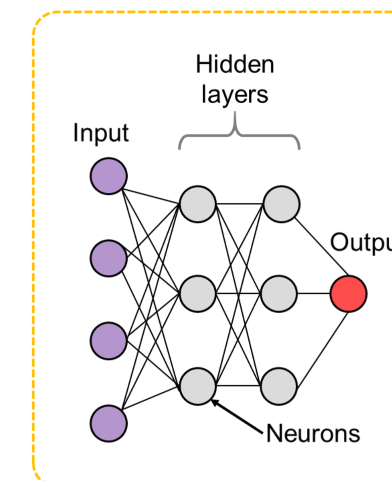
Ordinal Logistic Regression

- Ordinal logistic regression (OLR) is used when the categories are multiple and ordered.
- For example, the **4** ordered damage categories are 0=undamaged, 1=minor, 2=moderate, and 3=major.



Artificial Neural Network

- A typical ANN contains connected units or nodes known as artificial neurons.
- The network comprises of three main layers: the input layer, the hidden layer and the output layer. The hidden layer finds the relationship between input and the response variable.
- Five different ANN models are used namely ANN_10, ANN_25, ANN_50, ANN_100, and ANN_125 with respectively 10, 25, 50, 100, and 125 neurons.



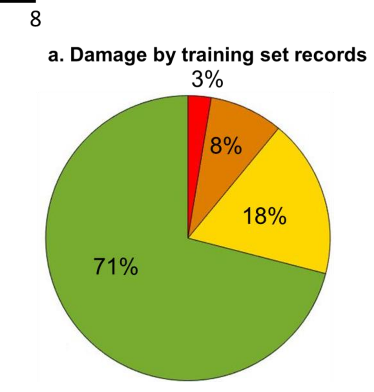
DATASETS

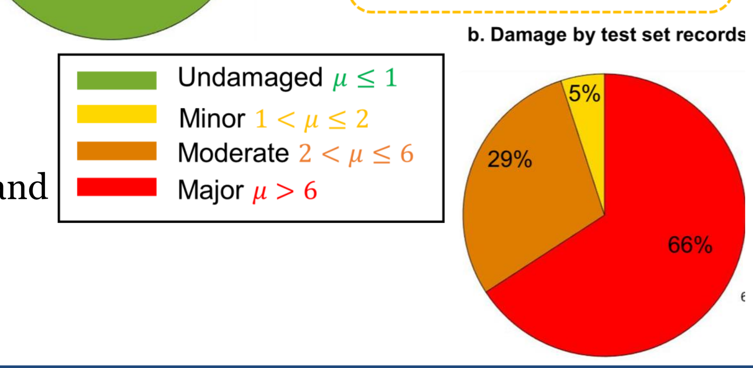
Training Set

- Response of ground motions from NGA-West2 database
- Selection criteria
  - Records from past 30 years
  - Records with PGA ≥ 0.01g
  - Not more than 20 records from same event
- 1,710 records matched selection criteria

Test Set

- Response of 120 scaled ground motions selected for a site in Oakland
- The ground motions represent three hazard levels: 50% ,10%, and 2% probability of exceedance in 50 years scenarios for that site

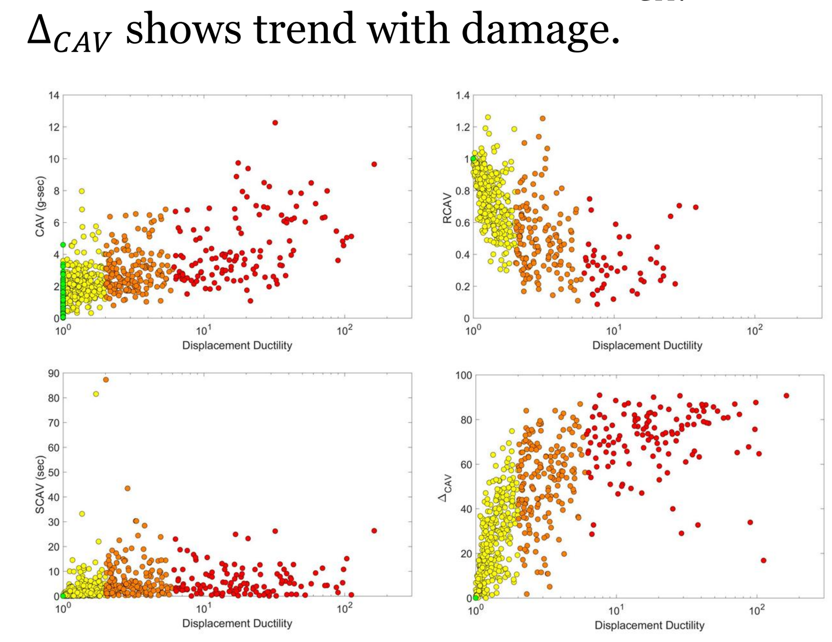




RESULTS

Damage Features vs. Damage States

Non linear time history analysis (NTHA) is performed on SDOF system with the training set and test set and proposed features are calculated. CAV, R_{CAV}, and Δ_{CAV} shows trend with damage.



SDOF Results

A comparative analysis of LR, OLR and ANN models is performed using CAV, R_{CAV} and Δ_{CAV} as features to find the ideal features and model. The highest accuracy is achieved by OLR with CAV and R_{CAV} as features.

Table 1. Accuracy of models with different features

Input Features	OLR	LR	ANN
CAV	36.60%	12.50%	21.60% (ANN_25)
R_{CAV}	60.00%	35.83%	50.83% (ANN_25)
Δ_{CAV}	61.67%	39.17%	40.83% (ANN_50)
CAV, R_{CAV}	74.17%	58.33%	59.17% (ANN_10)
R_{CAV}, Δ_{CAV}	63.33%	37.50%	55.83% (ANN_25)
CAV, Δ_{CAV}	69.17%	56.67%	63.33% (ANN_50)
CAV, R_{CAV}, Δ_{CAV}	68.30%	55.00%	70.00% (ANN_100)

MDOF Results

CAV and R_{CAV} for the MDOF system are calculated by performing NTHA using the training and test set ground motions. Using these features, OLR is trained first and then tested to detect the worst damage state occurrence and the location.

Table 2 Detection of worst damage state for MDOF test set

Damage condition	Number of occurrences	Detection accuracy
Major	82	90%
Moderate	32	75%
Minor	4	25%
Undamaged	2	100%
Overall	**120**	**84%**

97.5% accurate detection of worst damage location

CONCLUSION

- CAV, R_{CAV} combination produces the highest accuracy.
- Ordinal logit model produces higher accuracy than ANN models.
- For MDOF system, worst damage state detection has accuracy of **84%** (occurrence) and **97.5%** (location).
- Future work: data from instrumented structures will be used to assess damage.

This project was made possible with support from:

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