



### Structural Health Monitoring using Acceleration Data and Machine Learning Techniques

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### Outline

- Motivation and SHM background
  - CAV as a damage feature
    - CAV in Machine Learning
      - H-MC Framework for SHM
        - Conclusion

### **Motivation**

• Current US infrastructure systems need continuous monitoring.





Knowledge about damage → Decision:
1. Damage → plan proper response.
2.No damage → immediate occupancy.

### **SHM Process**

SHM is the process to develop online damage detection and/or assessment capability for engineered systems (aerospace, **civil**, mechanical).



### CAV & Damage



### CAV & Damage



20

40

Time (sec)

0

60

Roof --- 6<sup>th</sup> ..... 3<sup>rd</sup> - · 2<sup>nd</sup> - -

80

• Undamaged / baseline case from 1992 Landers earthquake

40 50 60

Time (sec)

10 20 30

Ground

0

# **CAV in Machine Learning**



Damage Identification

# Machine Learning (ML)

"ML is the science of making computers learn & act as humans to improve their learning over time in autonomous fashion, using data & information (observations & real-world interactions)."



### Supervised & Unsupervised Learning

- Supervised learning is inferring a function from **labeled training data**.
- Unsupervised learning is inferring function from **unlabeled training data.**
- Supervised learning
  - Regression continuous output
  - **Classification** discrete output
- Unsupervised learning
  - Clustering unknown output

**Classification Example** 



Features: words, characters, size, etc.

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### **Classification Example**



# **SDOF** Analysis

SDOF model	Feature Symbol	Theoretical Definition	Mathematical Definition	
m	CAVs	CAV value at a sensor	$CAV_{s} = CAV = \int_{0}^{T}  \ddot{u}(t)  dt$	
	R <sub>CAV</sub>	Ratio of floor CAV response to Linear CAV response	$R_{CAV} = \frac{CAV_s}{CAV_l}$	
(d)	S <sub>CAV</sub>	Change in effective duration compared to a linear model	$S_{CAV} = (D_{5-75,s} - D_{5-75,l}) \times 100\%$	
	$\Delta_{NCAV}$	Total absolute deviation of NCAV (Normalized CAV with $CAV_{max}$ ) compared to a linear model	$\Delta_{CAV} = \operatorname{abs}[(A_s - A_l)/A_l] \times 100\%$	

### SDOF Results: TEST-1

Input Features	OLR	LR	ANN_10	ANN _100	SVM
CAV	80.54	82.88	80.54	81.71	79.38
R <sub>CAV</sub>	87.16	86.72	88.72	89.49	88.33
$\Delta_{CAV}$	75.10	75.10	75.10	77.04	75.10
CAV, R <sub>CAV</sub>	90.27	89.44	88.72	90.66	91.05
$R_{CAV}, \Delta_{CAV}$	86.77	84.72	89.11	87.94	87.94
$CAV,\Delta_{CAV}$	80.54	83.27	80.54	81.32	79.38
CAV, $R_{CAV}$ , $\Delta_{CAV}$	90.27	89.05	90.27	90.66	89.88

 $CAV \& R_{CAV}$  used together as features give highest accuracy for both test cases

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### SDOF Results: TEST-2

	Input Features	OLR	LR	ANN_10	ANN _100	SVM
	CAV	36.67	12.50	18.33	15.83	8.33
	R <sub>CAV</sub>	60.00	42.50	30.83	37.50	20.83
	$\Delta_{CAV}$	61.67	45.00	42.50	40.00	21.67
hor	CAV, R <sub>CAV</sub>	74.14	61.67	18.33	40.00	25.00
	$R_{CAV}$ , $\Delta_{CAV}$	65.83	45.00	60.00	40.00	22.50
L	$CAV,\Delta_{CAV}$	70.00	60.00	51.67	36.67	24.17
ases	CAV, $R_{CAV}$ , $\Delta_{CAV}$	70.00	61.67	38.33	54.17	25.00

 $CAV \& R_{CAV}$  used together as features give highest accuracy for both test cases

### **MDOF** Analysis

### A MDOF model representing a 5-story structure





### > Class specific **recall** values for the two models

Class	MDOF-US	MDOF-NS
Undamaged	0.993	0.993
Minor	0.286	0.000
Moderate	0.781	0.463
Major	0.922	0.966

Locations were identified correctly even when damage locations were uncertain with CAV and R<sub>CAV</sub>

	MDOF model	Test set	Location accuracy
MDOF-US	TEST-1	97.5%	
	TEST-2	97.5%	
	TEST-1	93.0%	
	MDOF-N5	TEST-2	95.0%

# Human-Machine Collaboration (H-MC)

Human-Machine collaboration (H-MC) is a framework in which humans co-work with machines to complete specific tasks by using the particular strengths of both human (H) and machine (M).



# **Novelty Detection**

Between supervised and unsupervised learning, lies one class classification.

✓ Available data from only one class.





### Novelty model:

- Non-parametric (uncertain) distribution from training data
- Distance measure to detect novelty  $\geq 1.5 \times IQR$

**Limitation**: Novelty detection alone may result in False Positive (*FP*) due to lack of data from rare (strong but undamaging) shaking.

## **POE Envelope**



- Structure-specific SDOF model with basic data
- NTHA using 1,710 ground motions
- Joint distribution using  $CAV \& R_{CAV}$  of damaging

events

### H-MC for Damage Detection



### **CSMIP** Buildings

CGS CSMIP-12267 Hemet - 4-story Hospital CGS CSMIP-01260 El Centro - Imperial Co. Services CGS CSMIP-89494 CGS CSMIP-03603 San Diego - 19-story Commercial Bldg Eureka - 5-story Residential Bldg. CGS CSMIP-23634 San Bernardino - 5-story Hospital COS CSMIP-24322 CGS CSMIP-58354 History CSUH Admin. Bldg ALL PRIM CGS CSMIP-58019 Stanford - 4-story Residential E CGS CSMIP-57357 CGS CSMIP-24386 Van Nuys - 7-story Hotel CGS CSMIP-24463 San Jose - 13-story Govt Office Bldg Los Angeles - 5-story Warehouse 

# **Undamaged Buildings**



### **Undamaged Buildings**



### **Damaged Buildings**



### The Future



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