A Systems Approach to Wireless Structural Health Monitoring

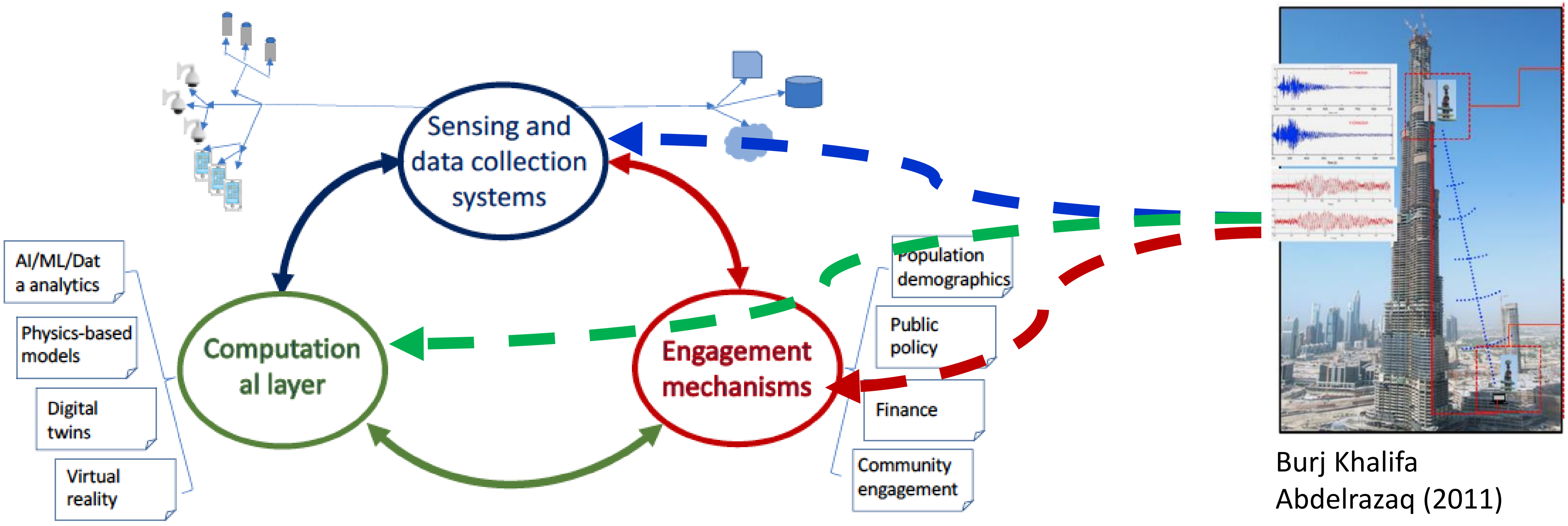
Anne S. Kiremidjian
Stanford University

EVACES 2023

10th International Conference of Experimental Vibration Analysis for Civil Engineering Structures
Politecnico di Milano, Italy - August 30 – September 1, 2023

POLITECNICO MILANO 1863

SHM Key to Smart and Sustainable Cities Metastructure



Burj Khalifa
Abdelrazaq (2011)

Kiremidjian and Lepech, (2023). A Metastructure Approach to Smart and Sustainable Cities, NAE, *The Bridge*, Vol. 53, No. 1. pp2-14.

The Structural Health Monitoring (SHM) System

- Main Components
  - Sensors – accelerometers, strain gages, tilt miters, temperature, pressure, etc.
  - Sensor network/ communication – wired and wireless networks
  - Data collection – local at sensor, local at structure, or remote data bank
  - Data interpretation – structural properties, damage diagnosis and prognosis
  - Information delivery – decision support

Structural Health Monitoring (SHM)

- Purpose – why monitor structures
  - Long-term deterioration
  - Extreme event effects
  - Smart City paradigm
    - Digital twins
    - Sustainable design
- Objective of SHM
  - Damage diagnosis
    - Detection
    - Localization
    - Classification
    - Quantification
  - Life prognosis
    - Residual strength
    - Residual life

Fundamental Approaches to Diagnosis

- Physics-based / System Identification
  - Uses a physical model of the structure
  - Uses data from multiple sensors distributed on the structure to identify changes in critical physical parameters
  - Computationally expensive
- Data – based models
  - Use data from a single sensors or several neighboring sensors
  - Tracks changes in the characteristics of the signals
  - Use advanced machine learning (ML), data science (DS) methods, artificial intelligence (AI)

Objective and outline of presentation

- Objective
  - Provide an overview of data-based models developed by our team
  - Show some examples
- Outline
  - Data-driven Algorithms:
    - Long-term/slow deterioration
      - Auto-regressive models
      - Wavelet-based energy models
    - Rapid-post-disaster assessment – all of the above plus
      - Residual displacement estimation
      - Maximum dynamic displacement estimation

Algorithms for long term deterioration damage and extreme events

- Autoregressive model with statistical significant testing
- Gaussian mixture model
- Wavelet transform – based Algorithms

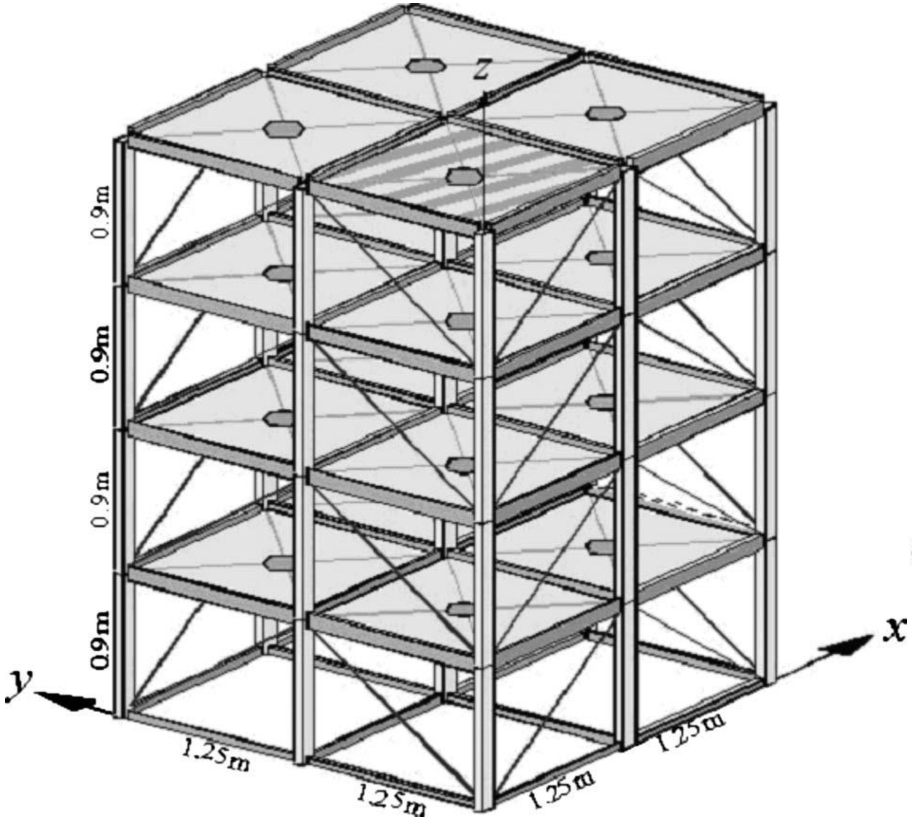
Auto-Regressive Moving Average (ARMA) Methods[1]

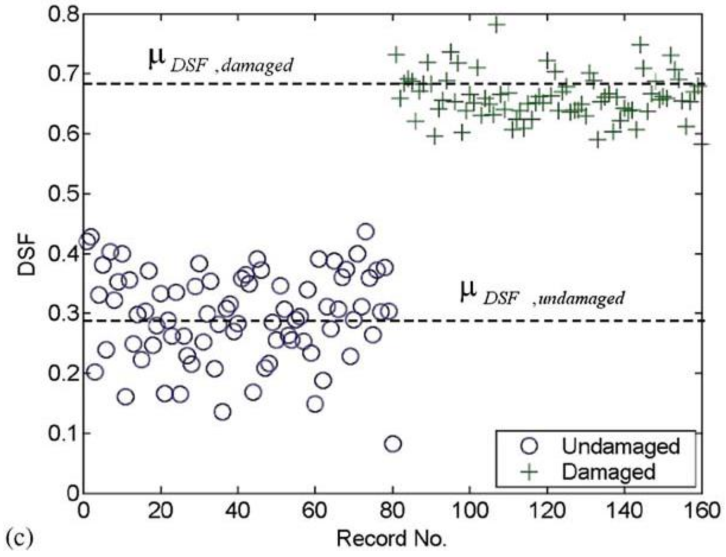
- Use pre-event and post-event ambient (low amplitude) vibrations
- Fit ARMA model to the signal that are normalized and standardized and use the AR coefficients
- Define Damage Sensitive Feature[2]
  - $DSF = \frac{\alpha_1}{\sqrt{\alpha_1^2+\alpha_2^2+\alpha_3^2}}$ where α_i are the first AR coefficients
  - Identify changes in DSF through *statistical significance testing*
  - Showed analytically that $|\partial\alpha_i/\partial\theta_i| \leq \Delta t/\sqrt{m_i k_i}$

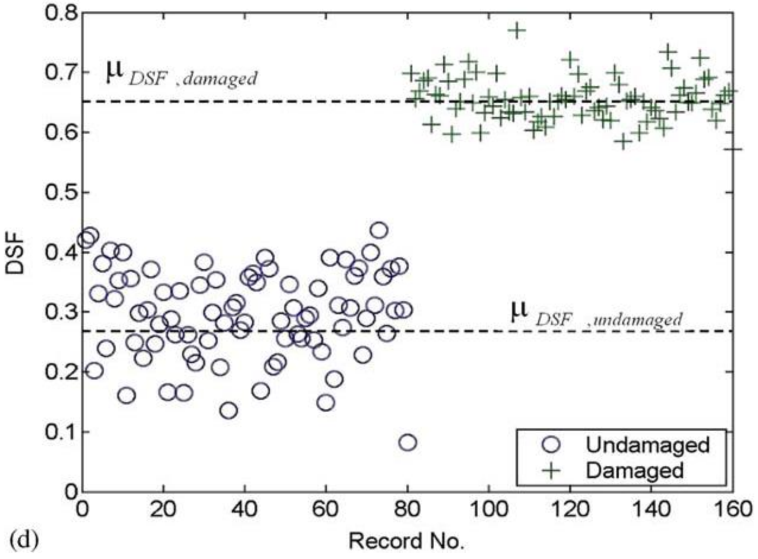
Refs: [1]Doebling et al., 1996; Sohn at al., 2001
[2]Nair at al., 2005, Nair and Kiremidjian, 2007, Nair at al., 2008

Example Application

- Application to ASCE Benchmark structure







Damage Pattern 3
All truss members removed
on floor 2

Damage Pattern 4
All truss members removed
on floor 2 and 4

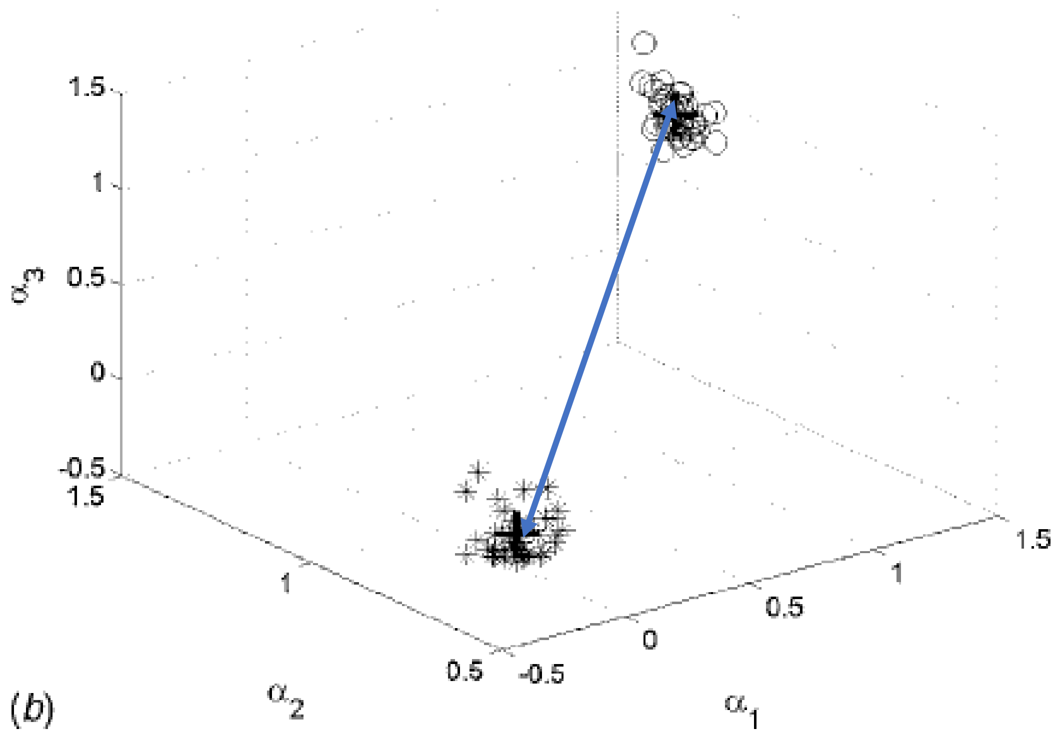
[2]Nair at al., 2005, Nair and Kiremidjian, 2007

ARMA Model with Gaussian Mixture MODEL

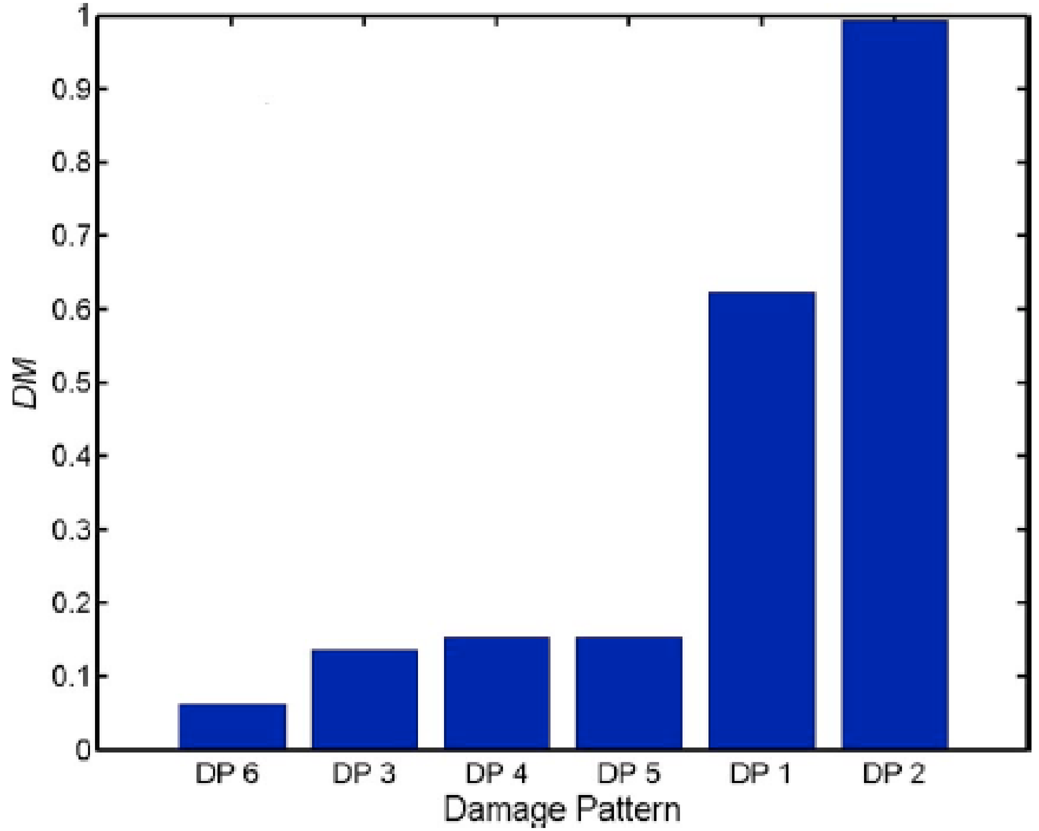
- ARMA Model – generate dataset of $\{\alpha_1, \alpha_2, \alpha_3\}$ from pre-and post event signals
  - Use Gap statistics to determine number of distinct clouds
  - Models clouds as Gaussian Mixture $f(X_{1:N}) = \sum_{i=1}^{M} \pi_i \phi_i(X; \theta_i)$
  - Define Damage Measure (DM) - the Mahalanobis distance between clouds
  - $\Delta(y, z{:}\,\Sigma) = \sqrt{(y-z)^T \Sigma^{-1} (y-z)}$
  - $DM = \frac{\Delta(\mu_{undamaged}, \mu_{damaged}, \Sigma_{undamaged})}{\Delta(\mu_{undamaged}, 0, \Sigma_{undamaged})}$

Nair and Kiremidjian, 2007

Example Application – ASCE Benchmark Structure



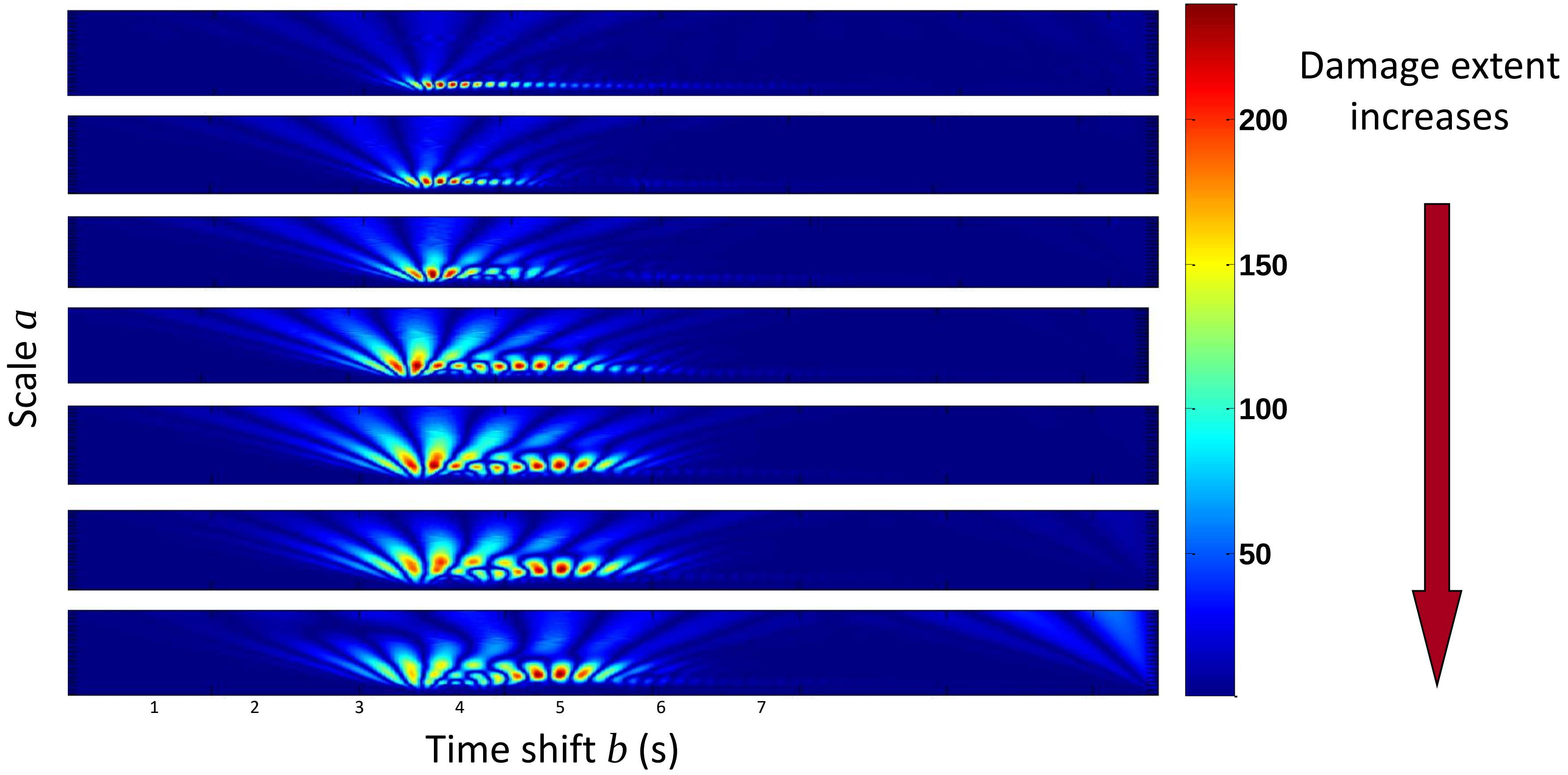
GMM for Damage Pattern 3 and undamaged structure



DM for each damage pattern

Wavelet coefficients of acceleration data

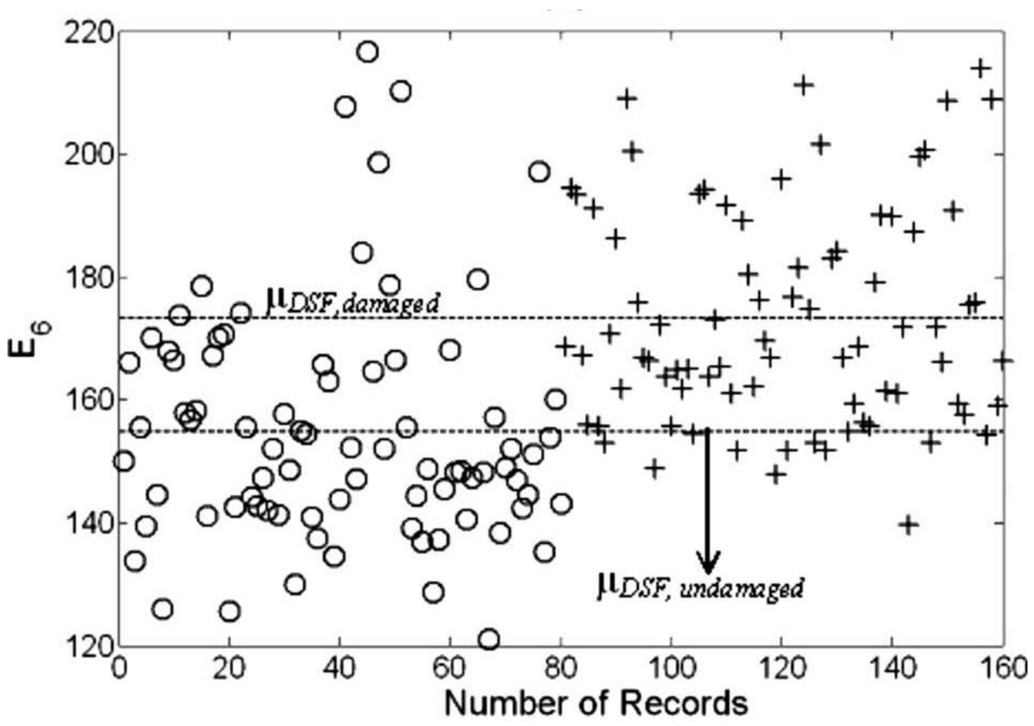
Haar, Debauche 2 and Morelet wavelet



Ridges shift in time (right) and scale (up)

Wavelet transform model

- DSF – function of wavelet energies
- $DSF = 1 - \frac{E_{scale(\hat{a})}}{\sum_{i=M}^{N} E_{scale(a^i)}}$
- Sensitivity of DSF

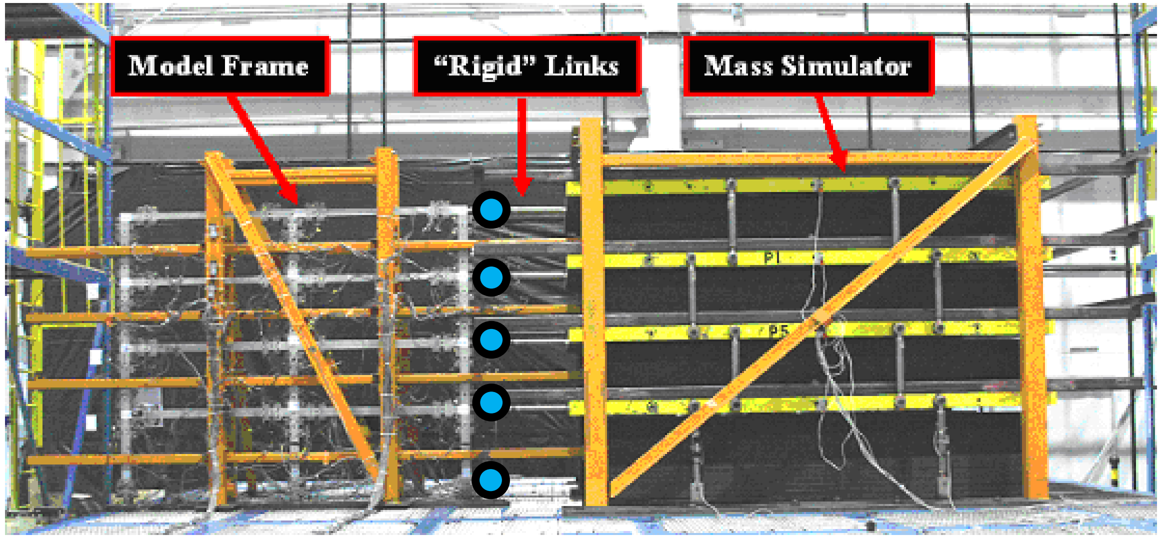


$$\frac{\partial CE}{\partial X} \cong \frac{\beta'}{2} \times \frac{(2\beta' - 3\alpha L - \alpha L^2) X^2 + 2\alpha L(L+1) X + \alpha L(1-L)}{(1-X)^2 \{\alpha L - (\alpha L - \beta') X\}^2} \propto \frac{1}{X^2}$$

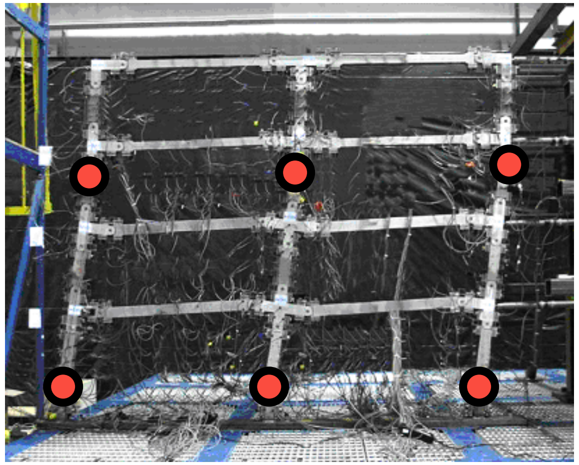
$X = \exp(-2\xi\omega_n)$ Where X<1

- Application to ASCE Benchmark Structure

Application: 4-Story Steel Moment Resisting Frame Test



T_1 =0.45sec
f_s = 128 Hz



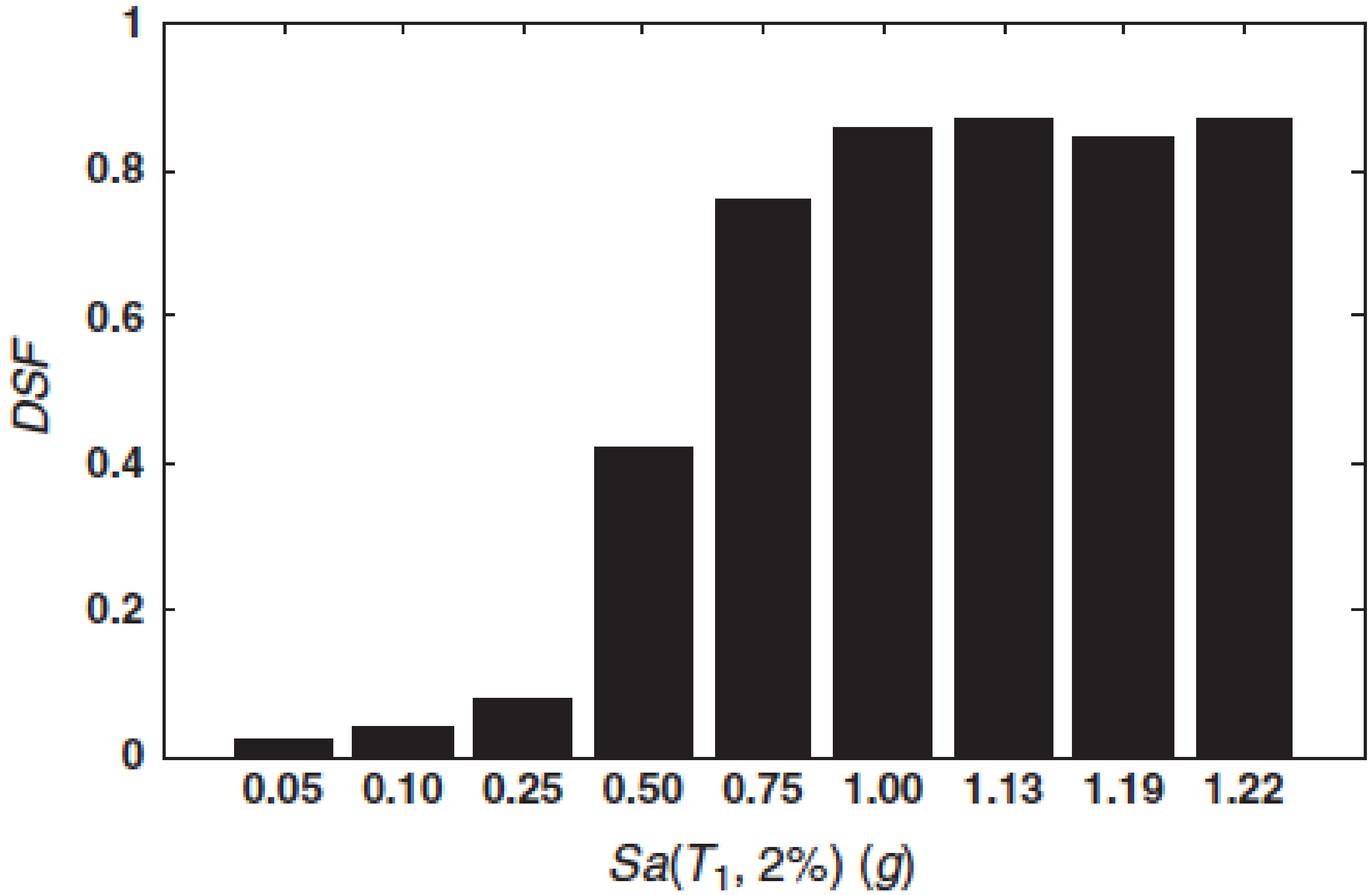
The frame is subjected to a series of scaled 1994 Northridge Earthquake motion

University at Buffalo (SUNY) Network for Earthquake Engineering Simulation (NEES)

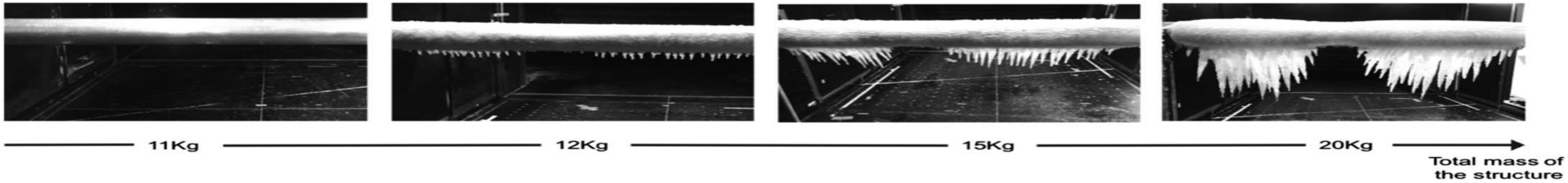
(Lignos D. G. et al. 2008. *Proc. 14th World Conference in Earthquake Engineering*)

Wavelet transform model

- Application to **four story steel moment frame** numerical model



Application to Ice Monitoring Experiment

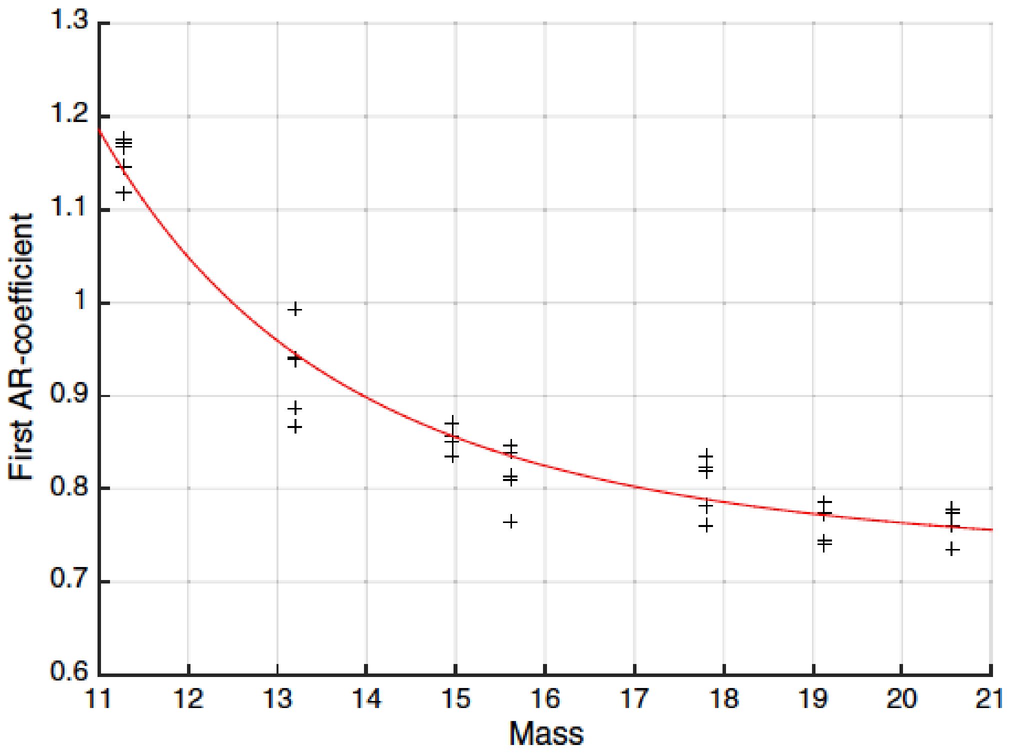


- Increase in weight due to icing recorded after each episode
- Vibration measurements obtained after each increase in icing
- Three algorithms applied
  - Peak Fourier frequency
  - DSF from AR coefficients
  - DSF from wavelet energy coefficients

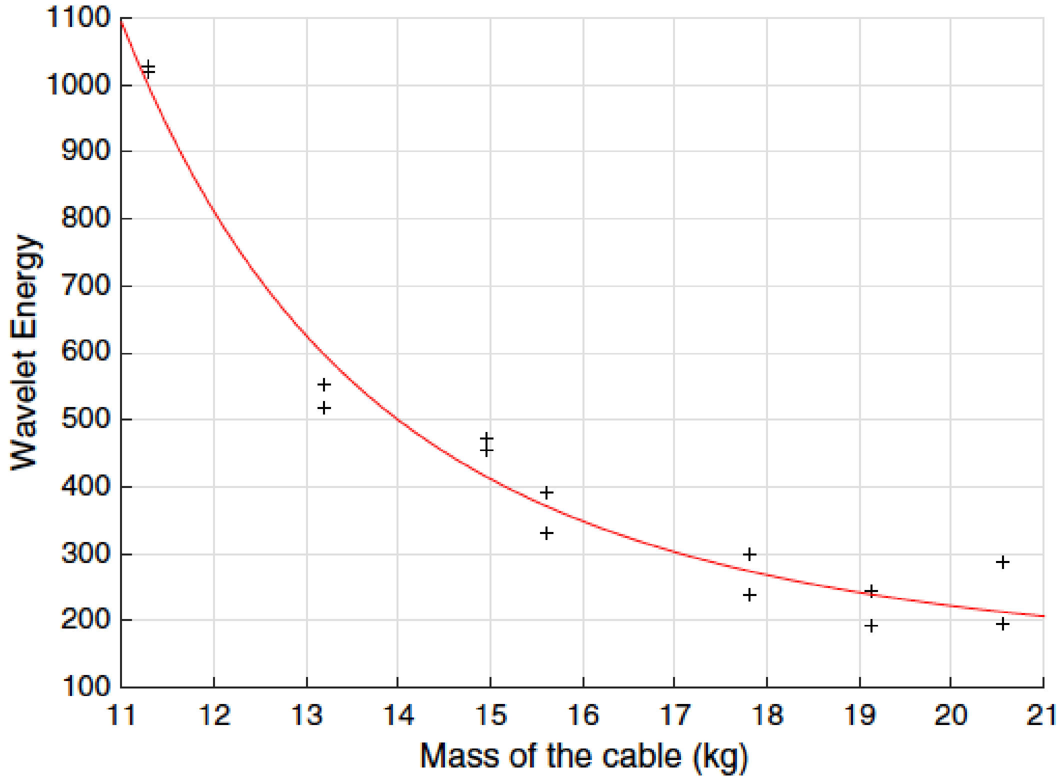
Andre, J., Kiremidjian, A. and Georgakis, C.,*ASCE J. Cold Reg. Eng.*, 2018, 32(2): 04018004

Correlation between ice mass and DSF

- DSF from AR coefficients



- DSF from Wavelet Energy



Comparison of Predictions

Table 4. Comparative Table of the Three Statistical Models

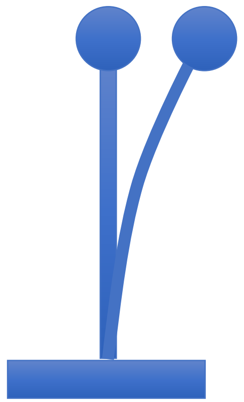
Statistical model	DSF	DSF variation (%)	Error (%)
Fourier transform analysis	First peak frequency	14	34
Autoregressive model	First AR coefficient	32	27
Wavelet transform analysis	Wavelet energy	68	10

Observation: The wavelet energy based DSF provides the highest variability and lowest error

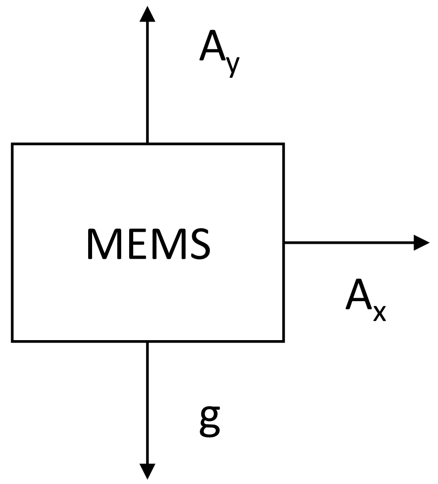
Algorithms for Rapid Damage Detection from Extreme Events

- Rotation/deformation algorithms for:
  - Residual displacement from *accelerometer* measurements
  - Deformed residual shape estimation using distributed sensors along the height of the structure
  - Maximum dynamic (transient) displacements from *accelerometer* and *gyroscope* measurements

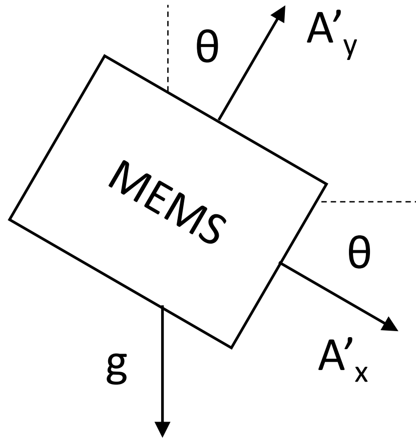
Rotation Algorithm Overview



- Sensor requirements:
  - Measurement in vertical and at least one horizontal direction
  - Capability to measure at the DC level
  - Accelerometer accuracy >1mg



Accelerometer aligned with gravity



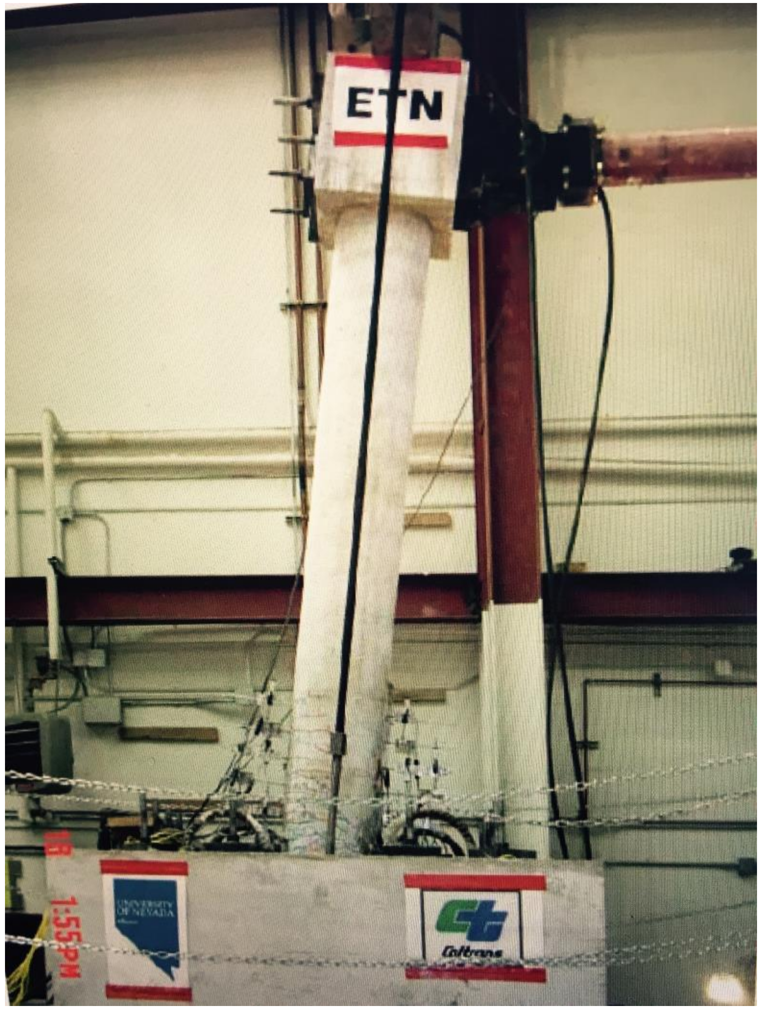
Accelerometer rotated

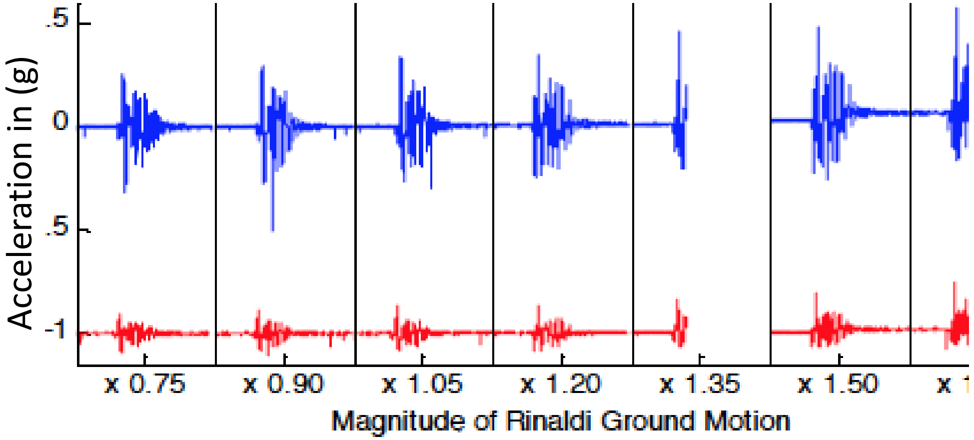
$$\theta = \arctan\left(\frac{A'_x}{A'_y}\right)$$

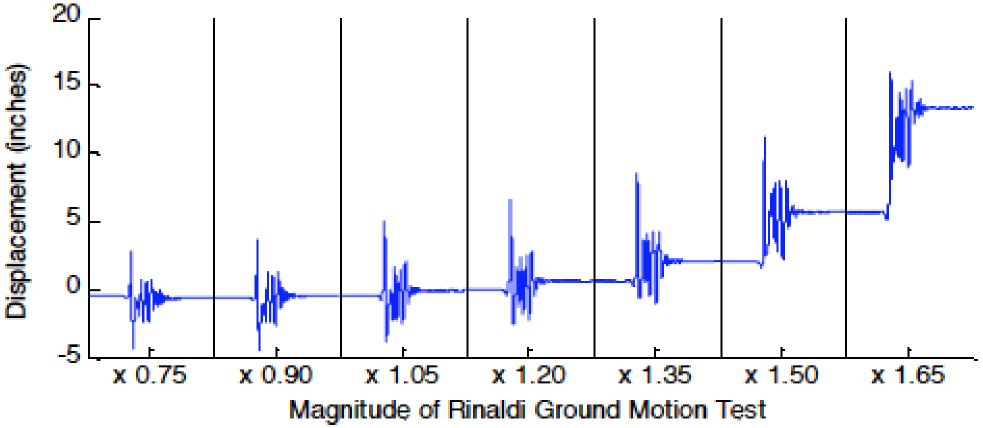
(Figures courtesy of Allen Cheung)

Single column experiment – University of Nevada, Reno

Observation during a single bridge pier experiment at University of Nevada, Reno

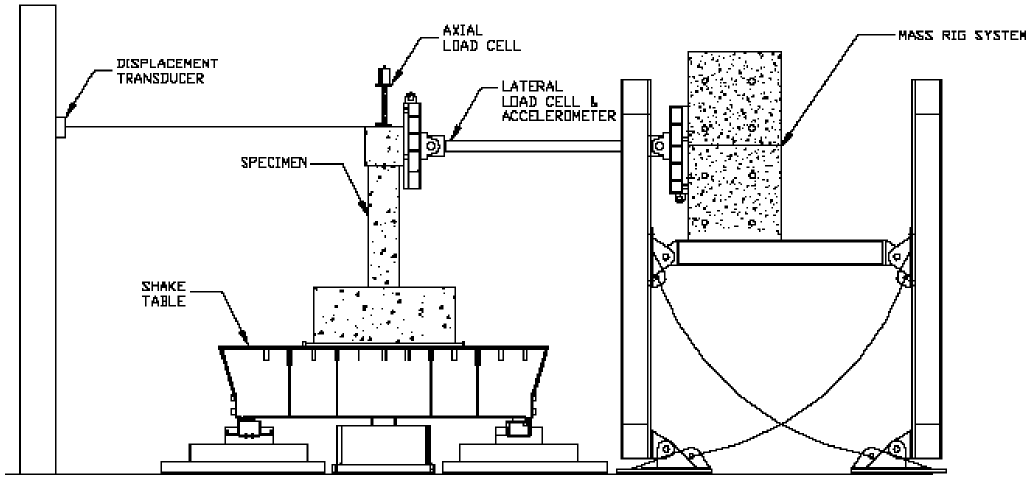




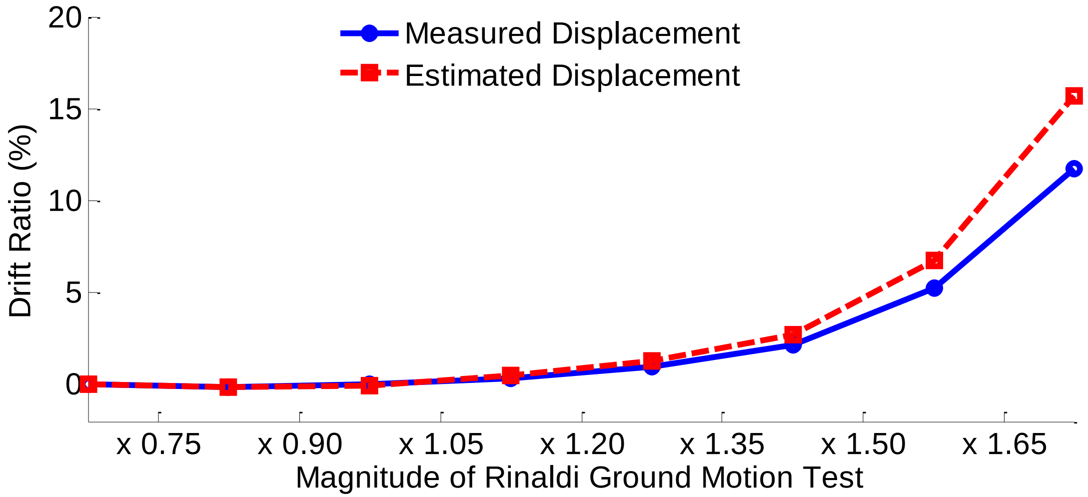


Experimental Validation 1: UNR tests

- Single sensor at the top of column – Test 1 University of Nevada Reno
- Estimate plastic hinge length
- Assume minimal curvature in column deformation



(Figure from Choi et al., 2007)

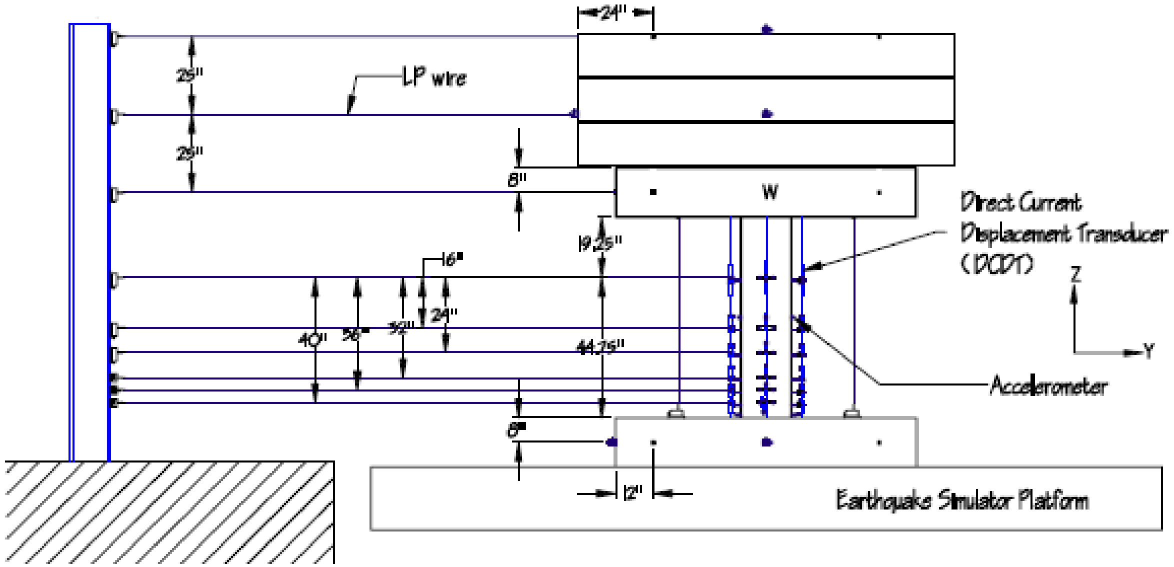


Cheung, A., and Kiremidjian, A. (2013). “Development of a Rotation Algorithm for Earthquake Damage Diagnosis, *Earthquake Spectra*, Vol. 30, No. 4, pp. 1381-1401.

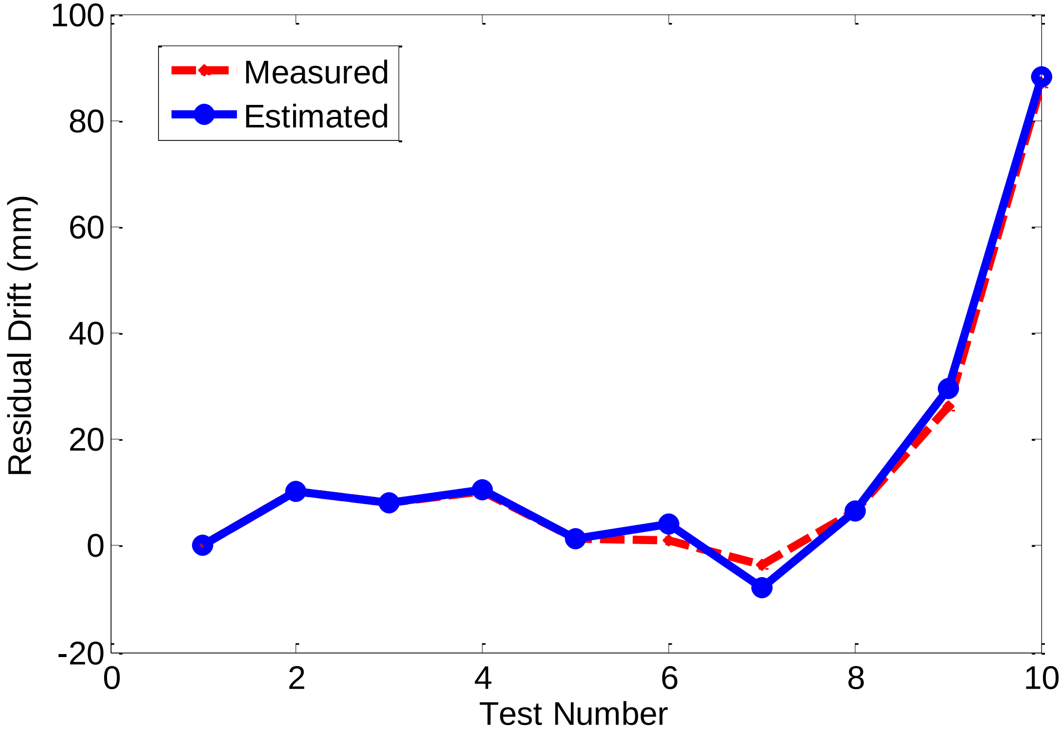
Multiple sensors along column height –

Test 2 University of California, Berkeley

Experimental Validation 2: UCB Tests



(Figure from Hachem et al., 2003)



Estimates from sensor on top of column

Cheung, A., and Kiremidjian, A. (2013). "Development of a Rotation Algorithm for Earthquake Damage Diagnosis, *Earthquake Spectra*, Vol. 30, No. 4, pp. 1381-1401.

Damage Classification

- Engineering Demand Parameter = residual displacement/drift
- Depend on structural system
- Examples: - FEMA P-58 methodology for the performance-based earthquake resistant design criteria

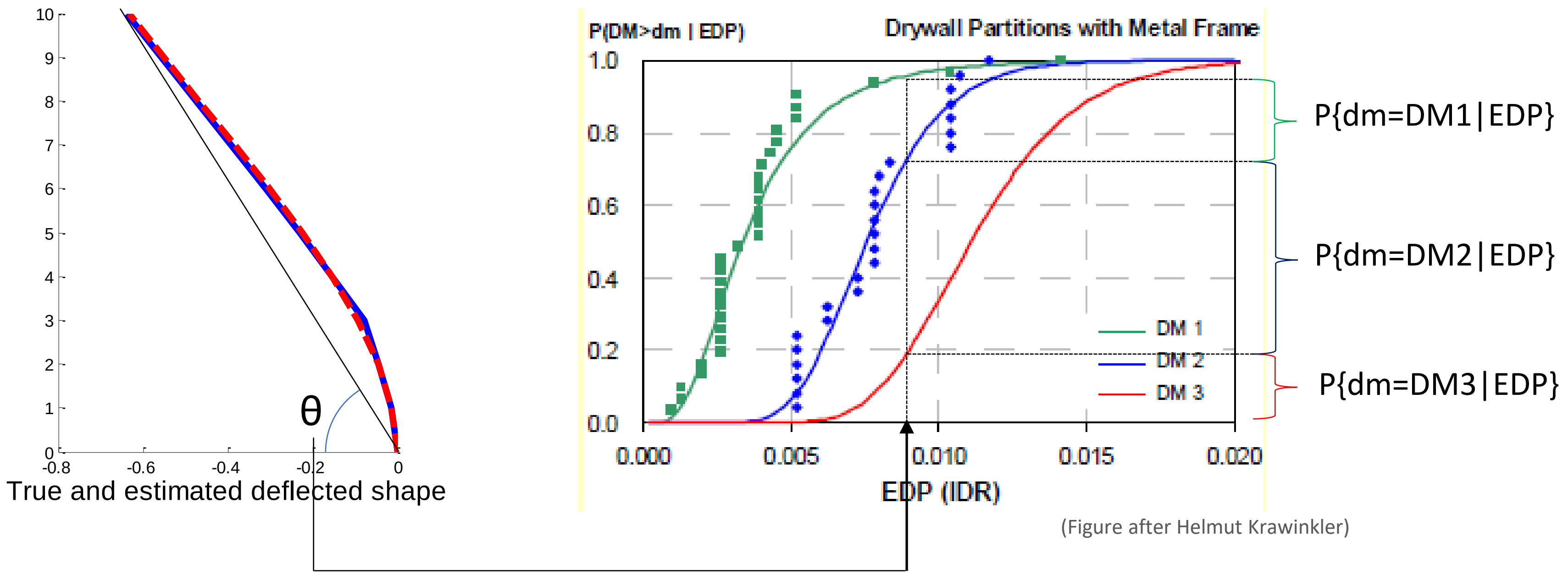
Table C-1 Damage States for Residual Story Drift Ratio

Damage State	Description	Residual Story Drift Ratio $\Delta / h^{(1)}$
DS1	No structural realignment is necessary for structural stability; however, the building may require adjustment and repairs to nonstructural and mechanical components that are sensitive to building alignment (e.g., elevator rails, curtain walls, and doors).	0.2% (equal to the maximum out-of-plumb tolerance typically permitted in new construction)
DS2	Realignment of structural frame and related structural repairs required to maintain permissible drift limits for nonstructural and mechanical components and to limit degradation in structural stability (i.e., collapse safety)	0.5%
DS3	Major structural realignment is required to restore margin of safety for lateral stability; however, the required realignment and repair of the structure may not be economically and practically feasible (i.e., the structure might be at total economic loss).	1%
DS4	Residual drift is sufficiently large that the structure is in danger of collapse from earthquake aftershocks (note: this performance point might be considered as equal to collapse, but with greater uncertainty).	High Ductility Systems $4\% < 0.5V_{design}/W$ Moderate Ductility Systems $2\% < 0.5V_{design}/W$ Limited Ductility Systems $1\% < 0.5V_{design}/W$

Notes: (1) h is the story height.

Residual displacement/drift is widely used as the Engineering Demand Parameter in fragility functions

- Damage classification

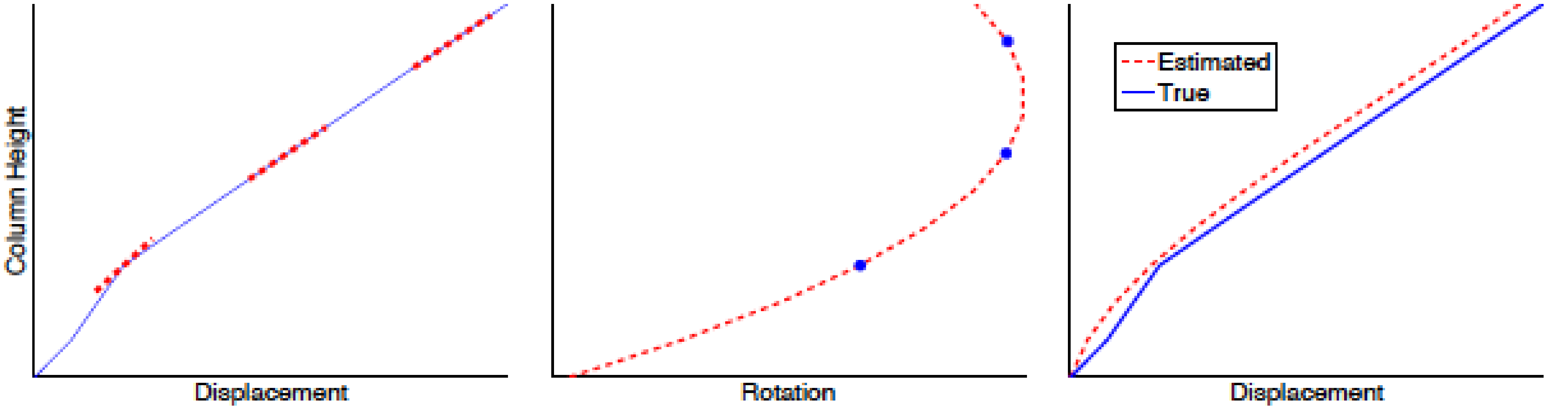


(Figure after Helmut Krawinkler)

Distributed Sensor Algorithm: Multiple-sensor

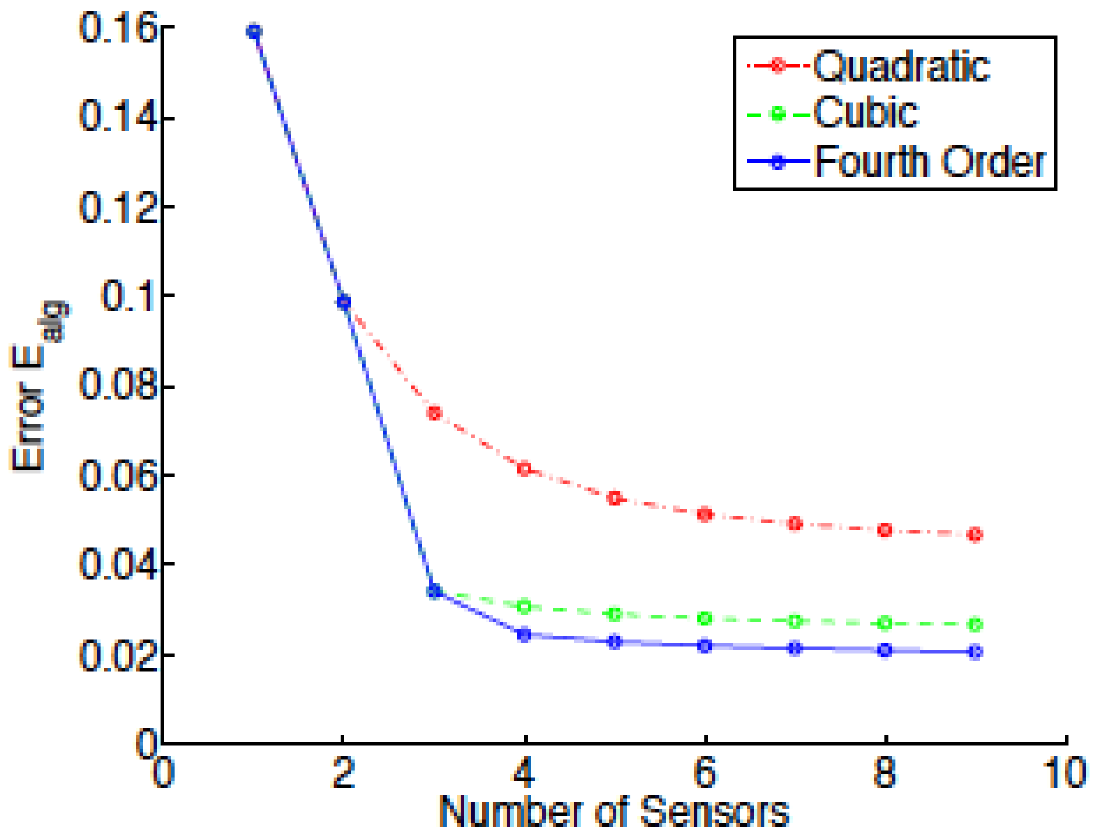
1. Deploy multiple sensors along structure
2. Obtain multiple rotation readings
3. Fit polynomial curve to rotations
4. Integrate polynomial curve to estimate displacements

Balafas, K. and Kiremidjian, A. (2015), *Structure and Infrastructure Engineering,* Vol. 11, No. 1, pp. 51-62.



(a) Rotation Measurement (b) Fitted Polynomial on Rotation Measurements (c) True and Estimated Deflected Shape

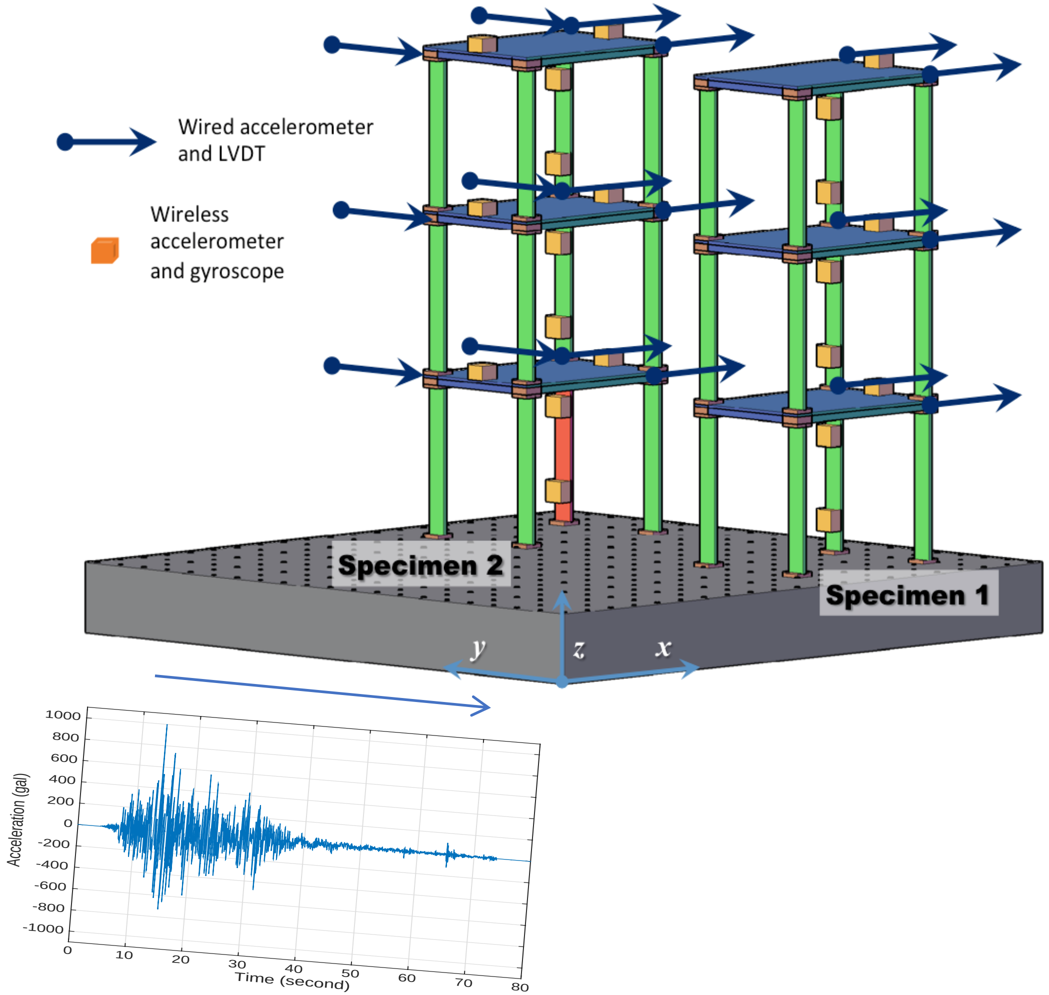
Mean algorithm error as function of number of sensors and polynomial order



(a) UNR Columns

Experimental set-up at NCREE, NTU

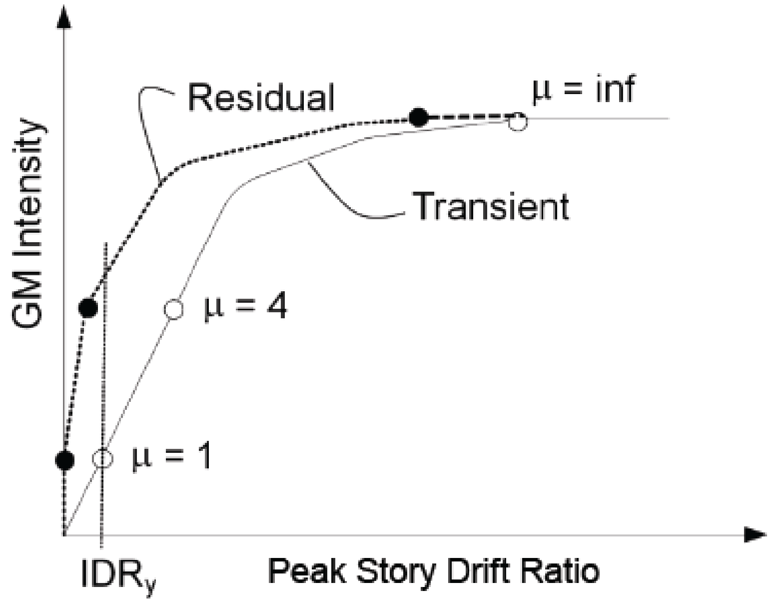
- Test 3: National Center for Research in Earthquake Engineering, National Taiwan University – Prof. C. H. Loh
- Two three-story steel moment frames
- Second frame – one column damaged
- Wireless sensors equipped with
  - 3D accelerometers and
  - 3D gyroscopes
- Direct displacement measurement at each story - LVDT



Damage quantification – depends on:

- Residual displacement
- Maximum <u>transient/dynamic </u>displacement

- Combined maximum dynamic displacements and residual displacement – more robust damage classification

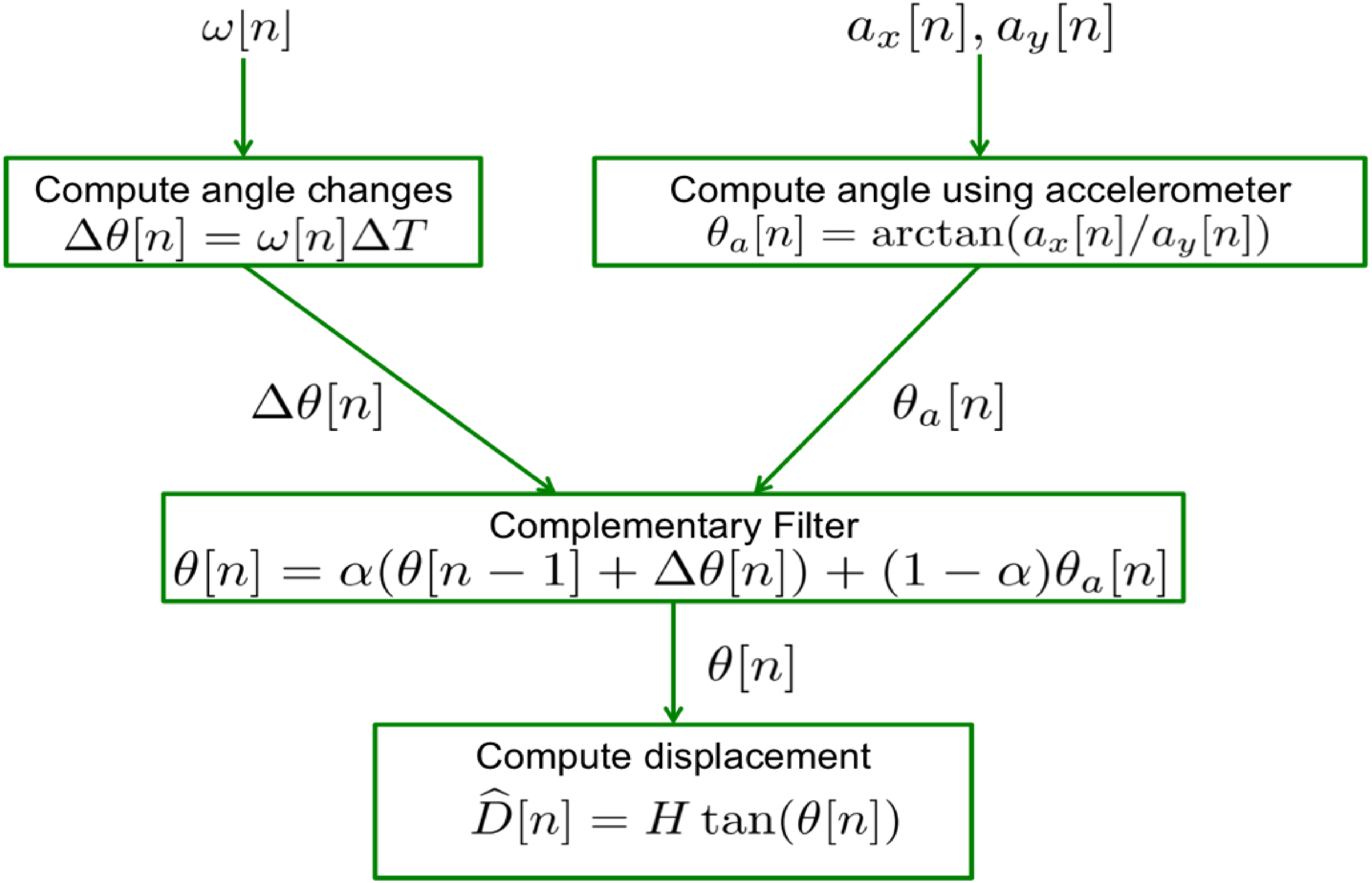


From FEMA P-58, 2012

Table C-2 Sample Transient Story Drift Ratios, Δ / h, associated with Damage State Definitions for Residual Drift

Sample Framing System	Δ_y / h	Δ / h			
		DS1[(1)]	DS2[(1)]	DS3[(1)]	DS4[(2)]
Steel ductile moment resisting frame	1%	1.5%	2.7%	4.1%	7.1%
Reinforced concrete shear wall	0.5%	1%	2.2%	2.6%	3.6%
Timber shear wall	1%	1.5%	2.7%	4.1%	5.1%

Displacement Estimation Algorithm

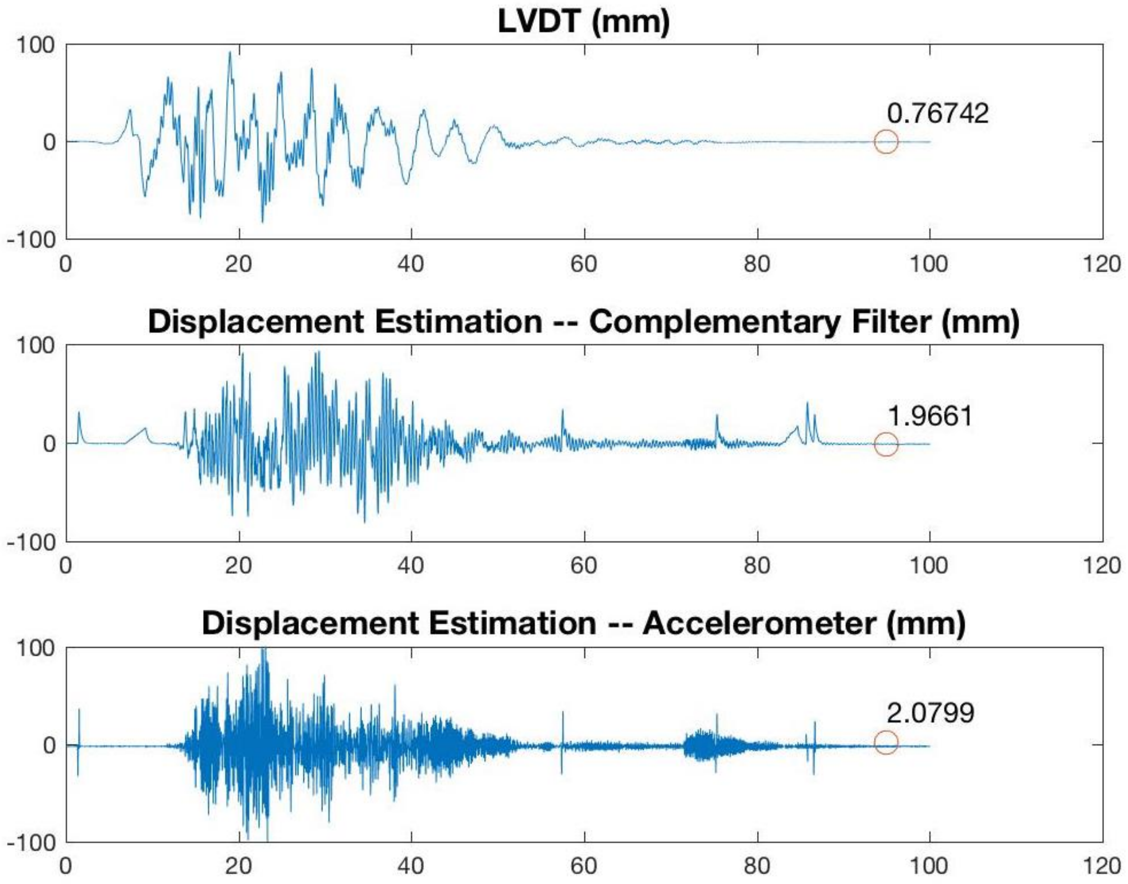


Measured vs. Estimated Displacements

- From LVDT
- Gyroscope with complimentary filter
- Accelerometer double integration

Specimen 1
Floor 1
Run 5

Dynamic displacement in mm



Time (s)

Peak dynamic displacement of Specimen 1 Floor 1.

- Good agreement of peak transient displacement

Run	LVDT (mm)	Complementary Filter (mm)	Accelerometer (mm)
1	14.8653	20.8089	22.4400
2	41.7862	45.0247	47.8257
3	59.5295	60.9200	62.9520
4	79.9475	81.1538	85.0782
5	92.4409	93.8918	114.8937
6	117.3312	116.5927	163.7939
7	126.4404	128.4456	145.4661

Summary and Conclusions

- Data-based algorithms can be effective in determining damage
  - From long-term deterioration
  - From extreme event/load occurrences
- Data-based algorithms are computationally efficient
- Data-based algorithms can be easily embedded on a microchip to provide on-board near-real time assessments leading to alerts
- Localization and quantification remain a challenge
- More experimentation needed
- More validation needed

Acknowledgments

- Stanford Students:

  Krish Nair
  Hae Young Noh
  Allen Cheung
  Konstantinos Balafas
  Julia Andre
  Yizheng Liao

National Science Foundation

NEES

George E. Brown Jr. Network for Earthquake Engineering Simulation

Collaborations:

- University of Nevada, Reno
  - Prof. Saiid Saiidi and his students
- University of California, Berkeley
  - Prof. Steve Mahin
- National Taiwan U. - NCREE,
  - Prof. C. H. Loh and his students
- Denmark Technical University & Aarhus University
  - Prof. Christos Georgakis
- Los Alamos National Labs
  - Dr. Charles Farrar

Thank You!