Machine Learning-Based Low Cycle Fatigue Techniques for Reinforcing Bars

ACI Convention Spring 2024

03-25-2024

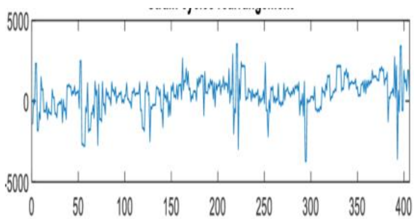
Naga Lakshmi Chittitalli and Islam M. Mantawy*

*Assistant Professor

Civil and Environmental Engineering
Henry M. Rowan College of Engineering
Rowan University

Background

Strain from reinforcing steel bars

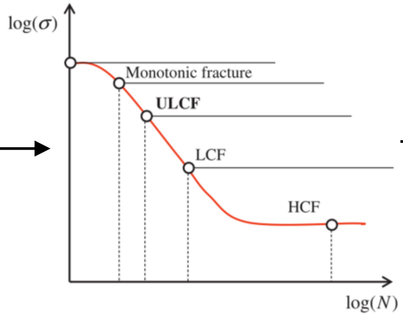


Rainfall counting method

Strain cycles

Empirical Equations

Fatigue life



Palmgren-Miner rule

Damage detection

Traditional Approaches

Traditional approach

- **Strain to Strain Cycles:** Using the rain-flow counting method
- **Empirical Equations:** Using empirical equations, including Mander's equation
- **Fatigue Damage Models:** Usage of fatigue damage models, like the Palmgren-Miner damage rule, for manual damage prediction.

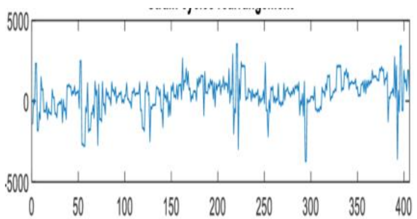
Objectives

The main objective of the study is to transform the traditional method of predicting damage of reinforcing steel bars to an advanced automated method.

Background

Can ML Transform low-cycle fatigue estimation

Strain from reinforcing steel bars

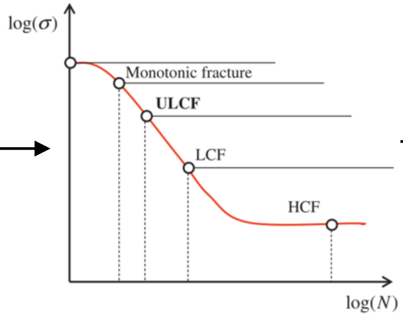


Rainfall counting method

Strain cycles

Empirical Equations

Fatigue life



Palmgren-Miner rule

Damage detection

Traditional Approaches

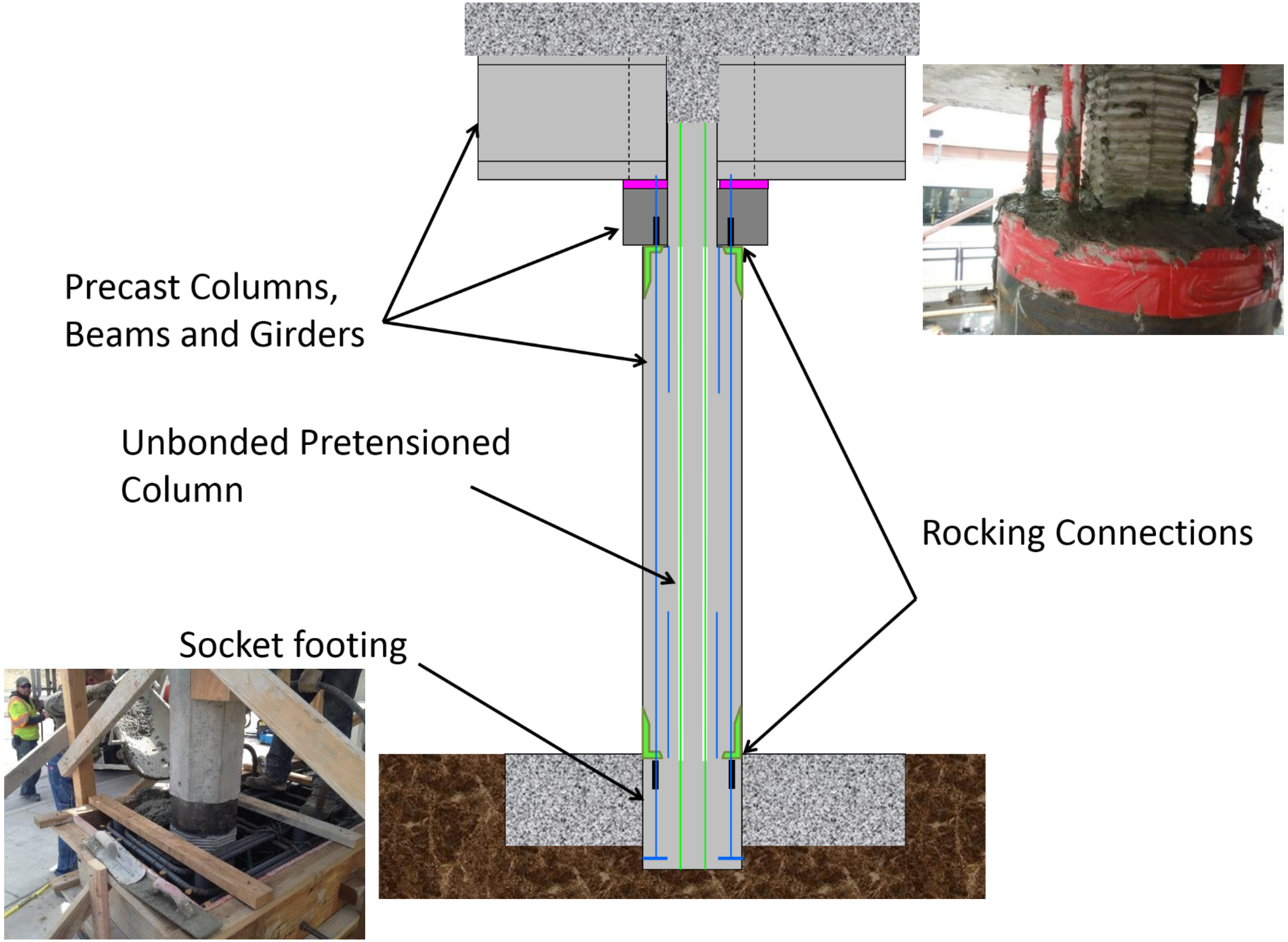
Traditional approach

Objectives

The main objective of the study is to transform the traditional method of predicting damage of reinforcing steel bars into an advanced automated method.

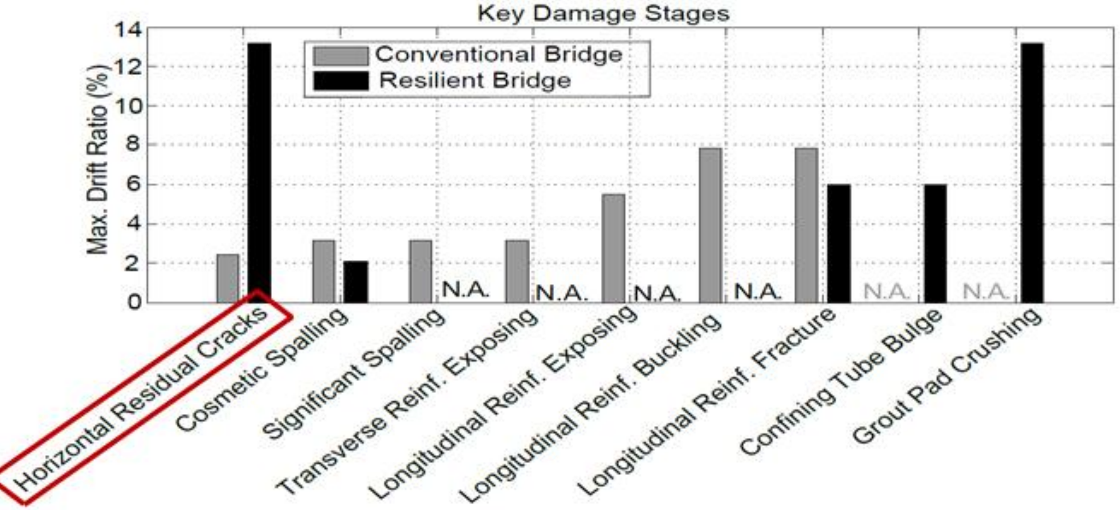
- **Strain to Strain Cycles:** Using the rain-flow counting method
- **Empirical Equations:** Using empirical equations, including Mander's equation
- **Fatigue Damage Models:** Usage of fatigue damage models, like the Palmgren-Miner damage rule, for manual damage prediction.

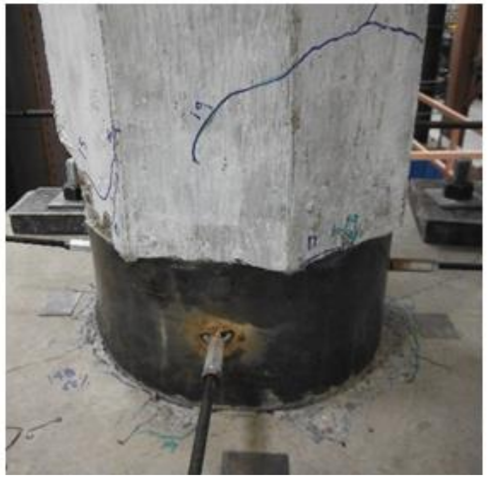
Test Bed


Precast Columns,
Beams and Girders
Unbonded Pretensioned
Column
Socket footing
Rocking Connections

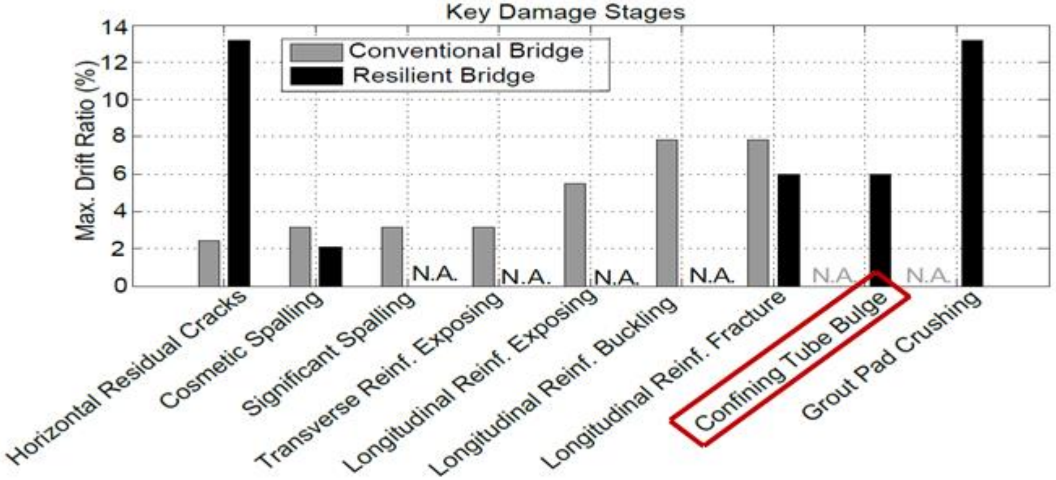
Test Bed

Test Bed



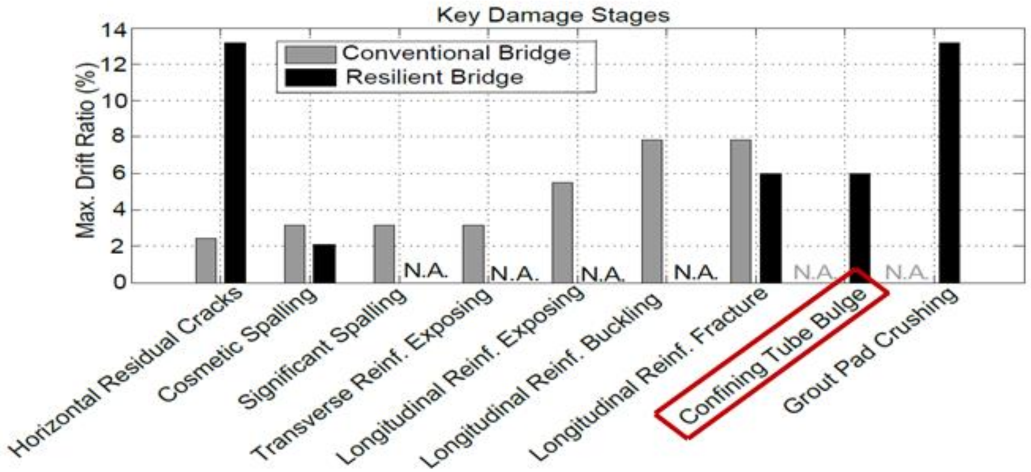


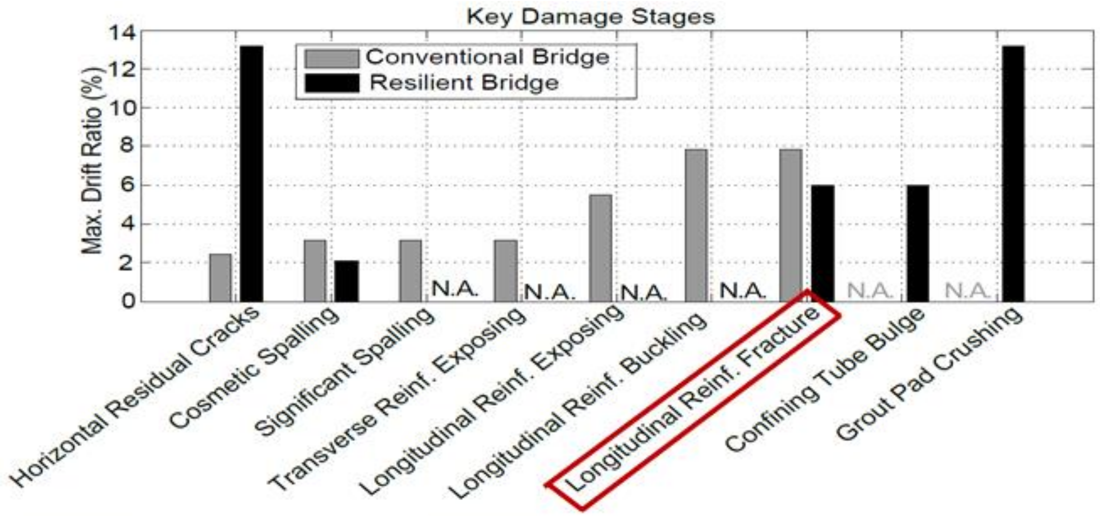
Only occurred at 13% drift with hairline width



Can be controlled by using thicker tube wall

Test Bed





Can be controlled by using thicker tube wall

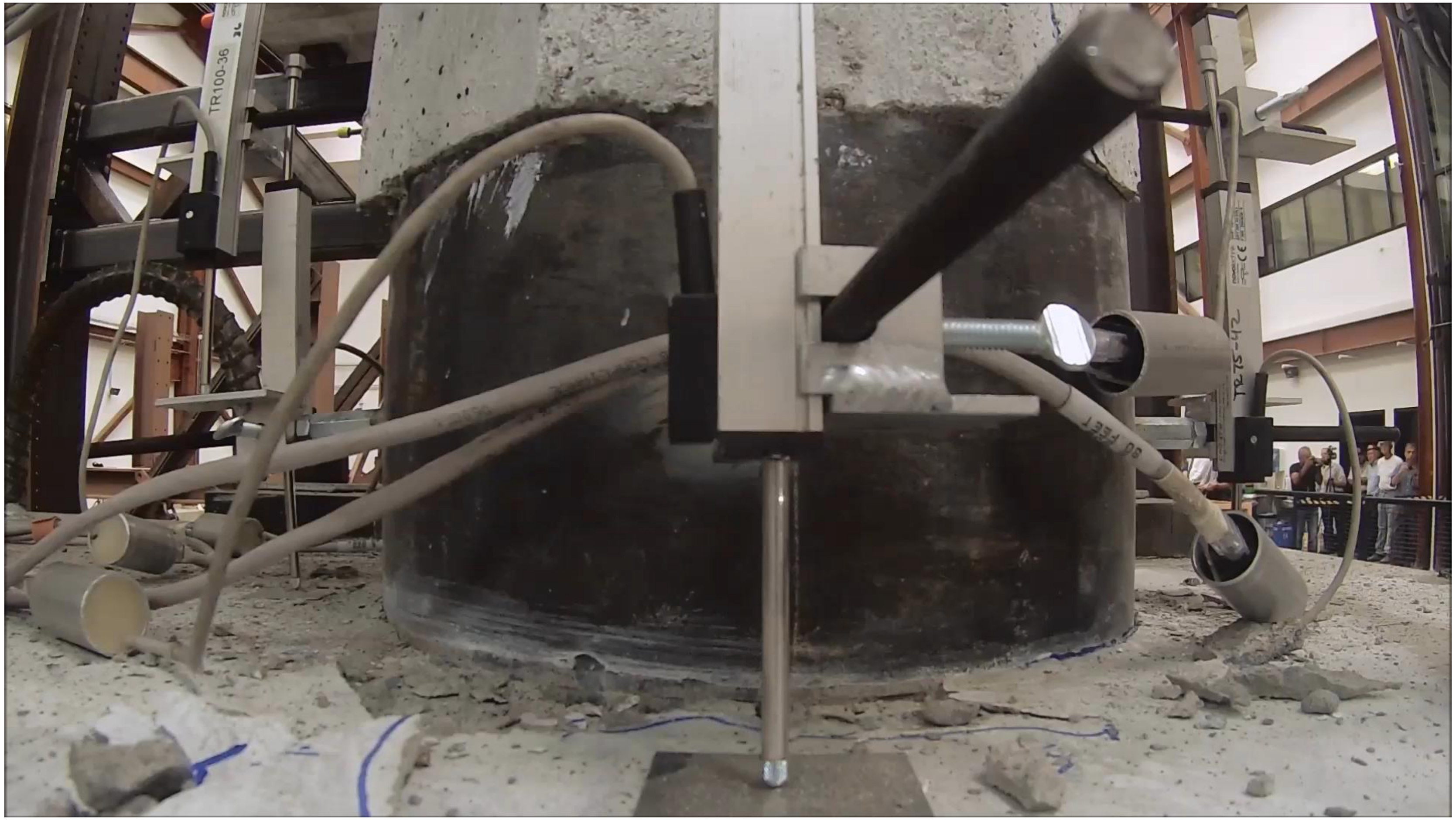
PROBLEM

Evaluate

Simulate

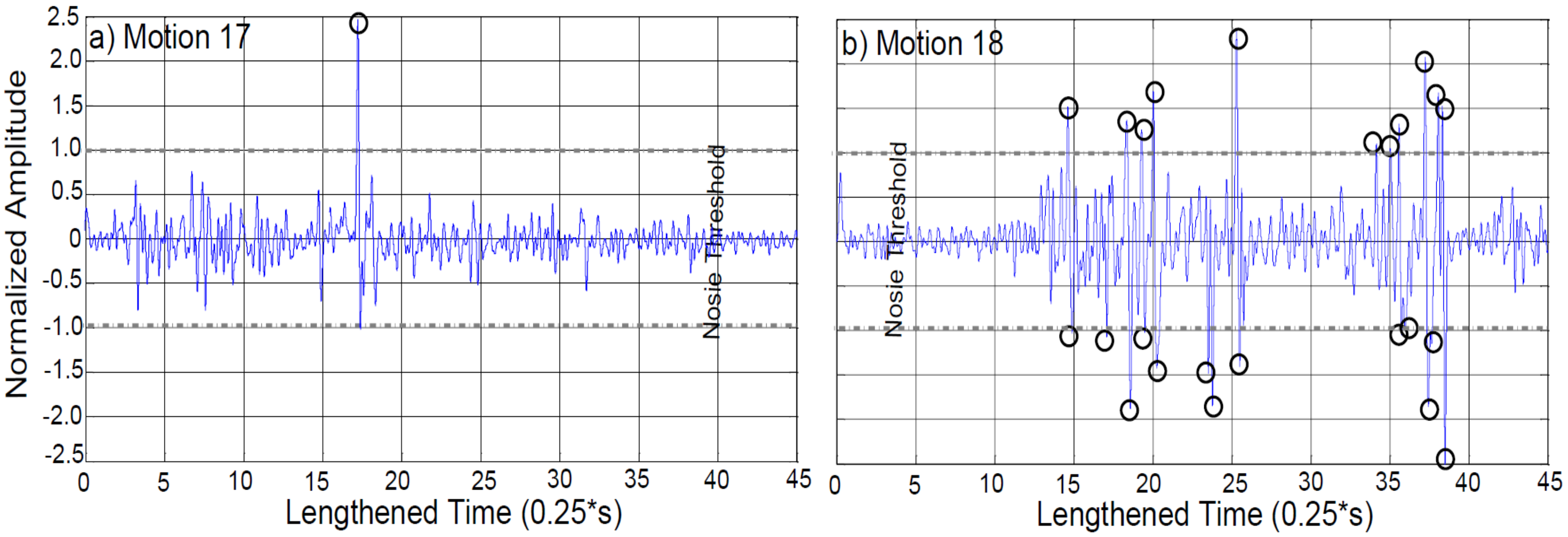
Enhance

Test Bed



Test Bed

Test Bed



Motion	17	18	19	20A	20B	21A	21B	21C	Total
# of Fractures	1	24	29	5	5	0	1	5	70

Method 1:
Fracture Estimation by Acoustic Emissions

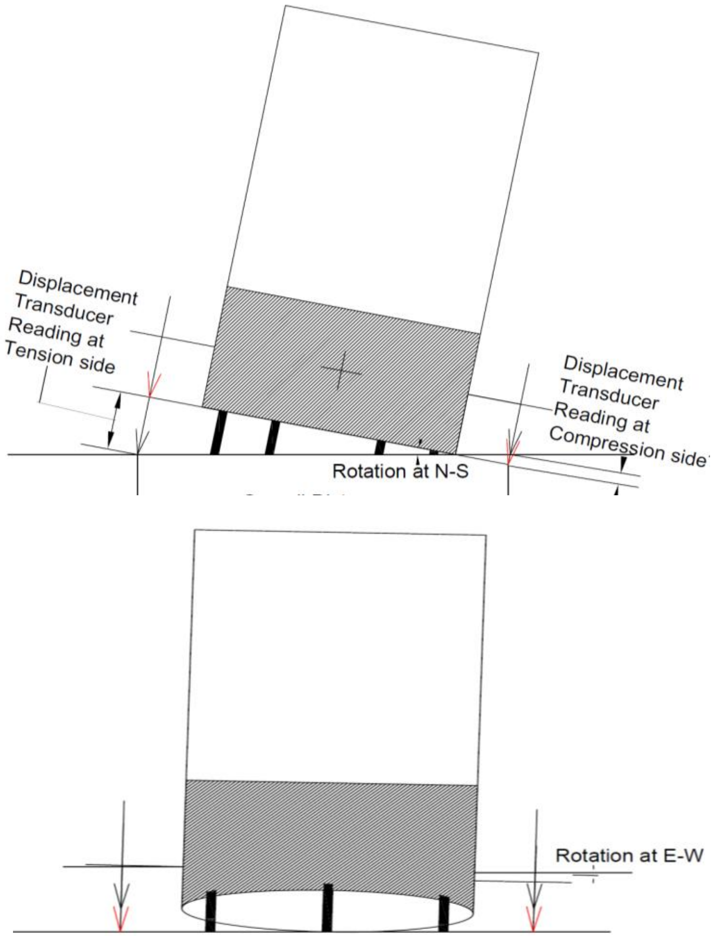
Strain Estimation

1- Bar buckling in the columns was inhibited by a confining tube detail;

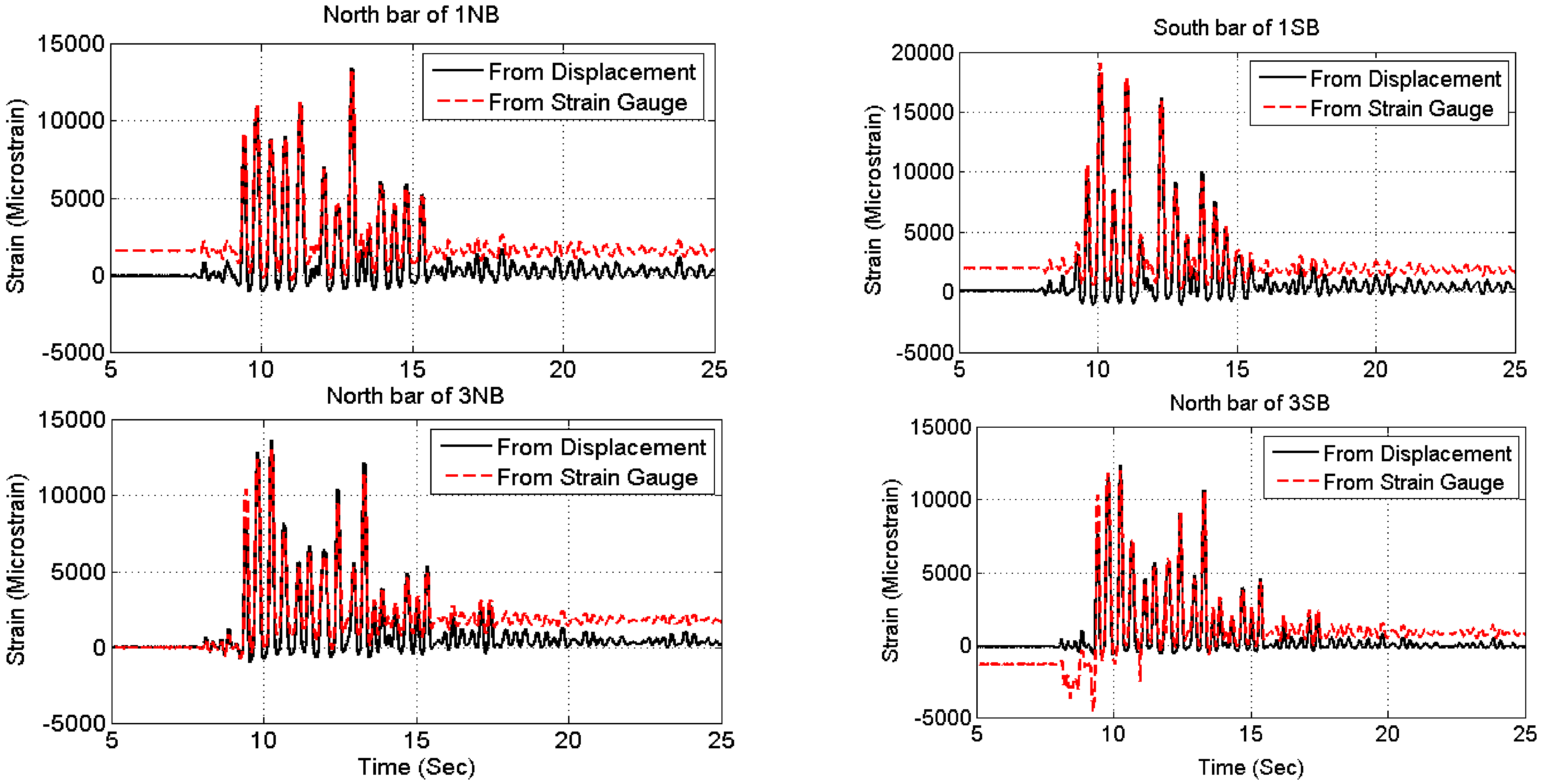
2- Strains in the reinforcement were distributed over deliberately debonded lengths;

3- All 72 of the column's longitudinal reinforcement fractured during testing; and

4- Because the system deformed by rocking, the strain response histories could be calculated from the measured rotations at columns' ends after the deformation capacities of the strain gauges were exceeded.



Strain Estimation



Estimation of Fracture of Reinforced Bars

Estimate the bar elongation history using the Displacement Method (Elong.)

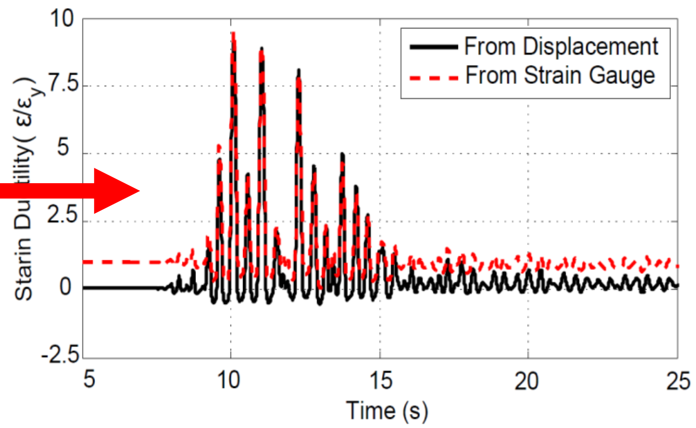
Calculate the bar strain history using the debonded length (Strain)

Verify the calculated strain history with strain gauge reading

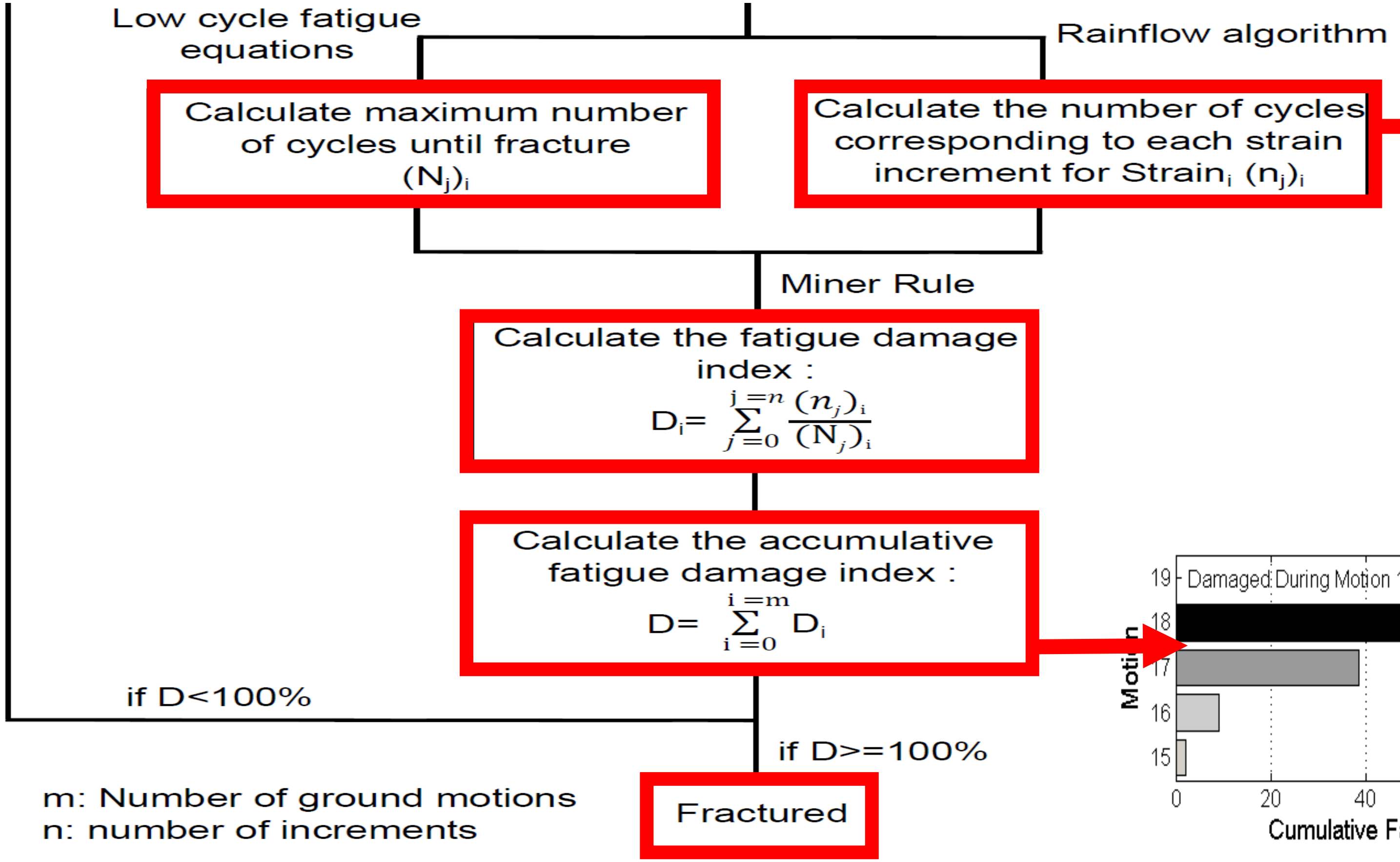
Use Motion (i+1)

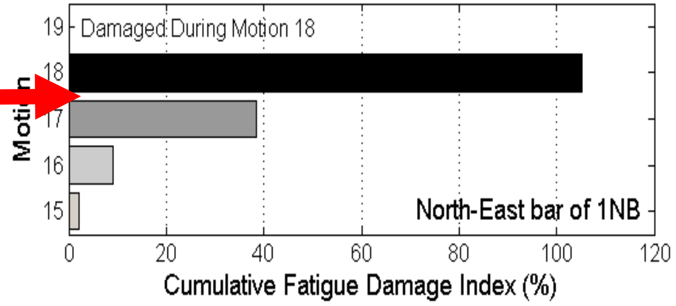
Get the strain history for motion (i) ($Strain_i$)

Increment the strain history into series of strain $increment_j$ $0.1\,\varepsilon_y$

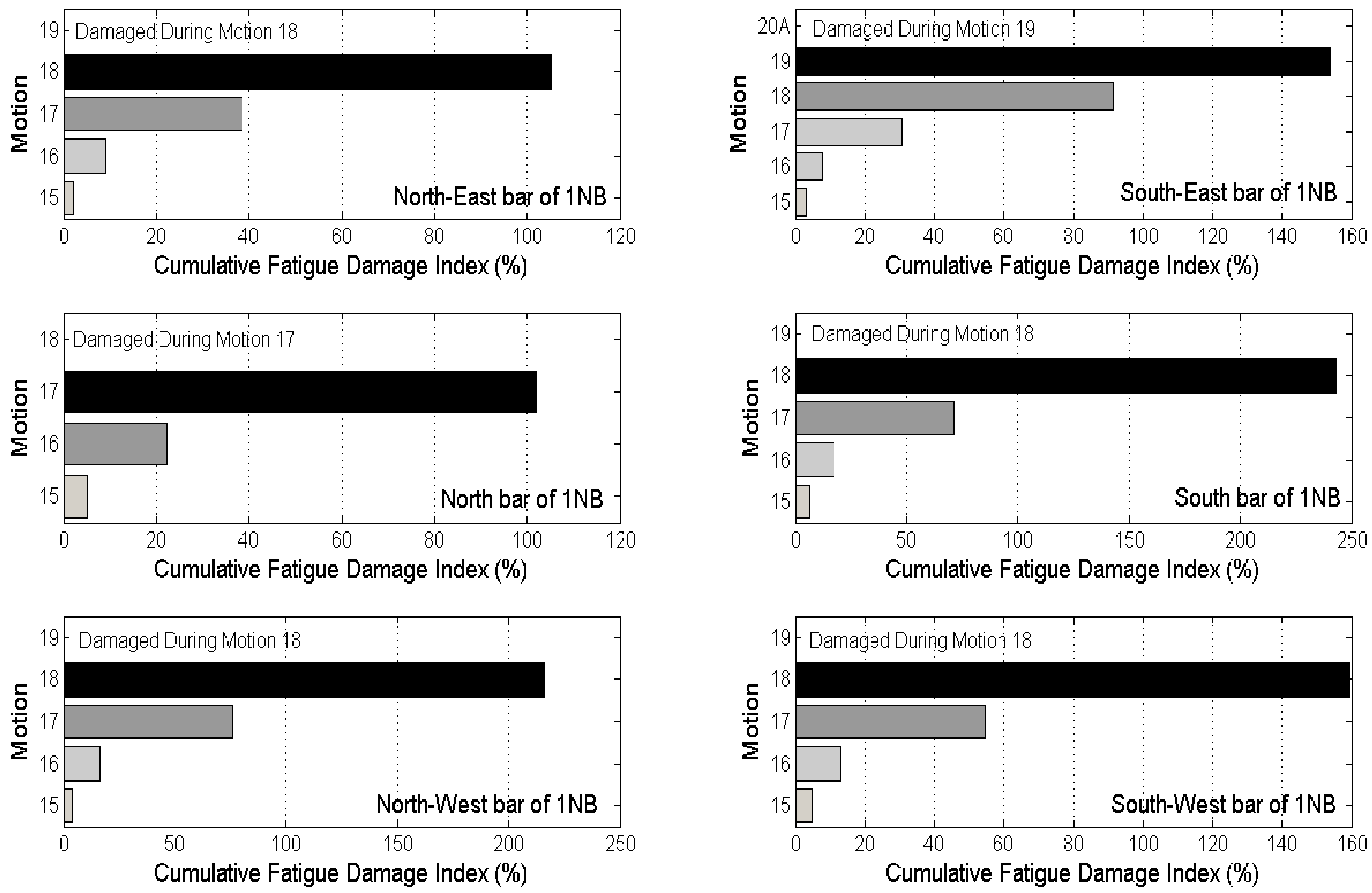


Estimation of Fracture of Reinforced Bars

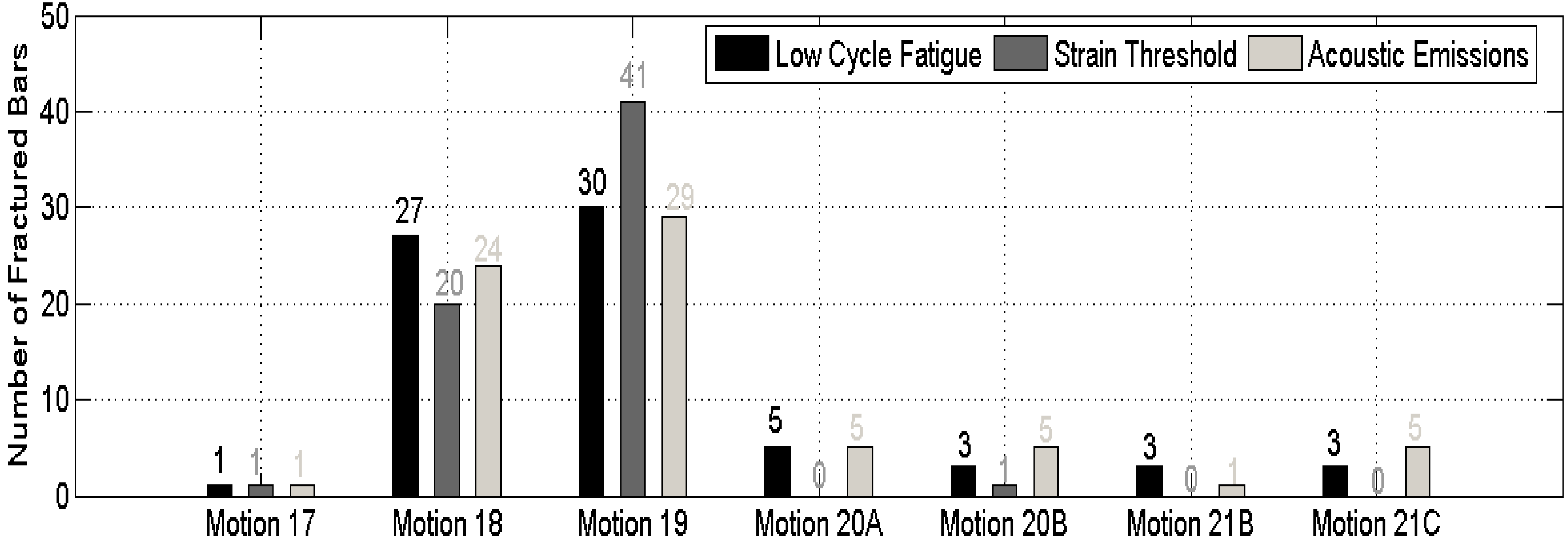




Estimation of Fracture of Reinforced Bars



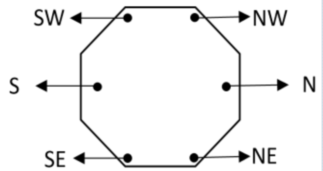
Fracture Estimation Summary

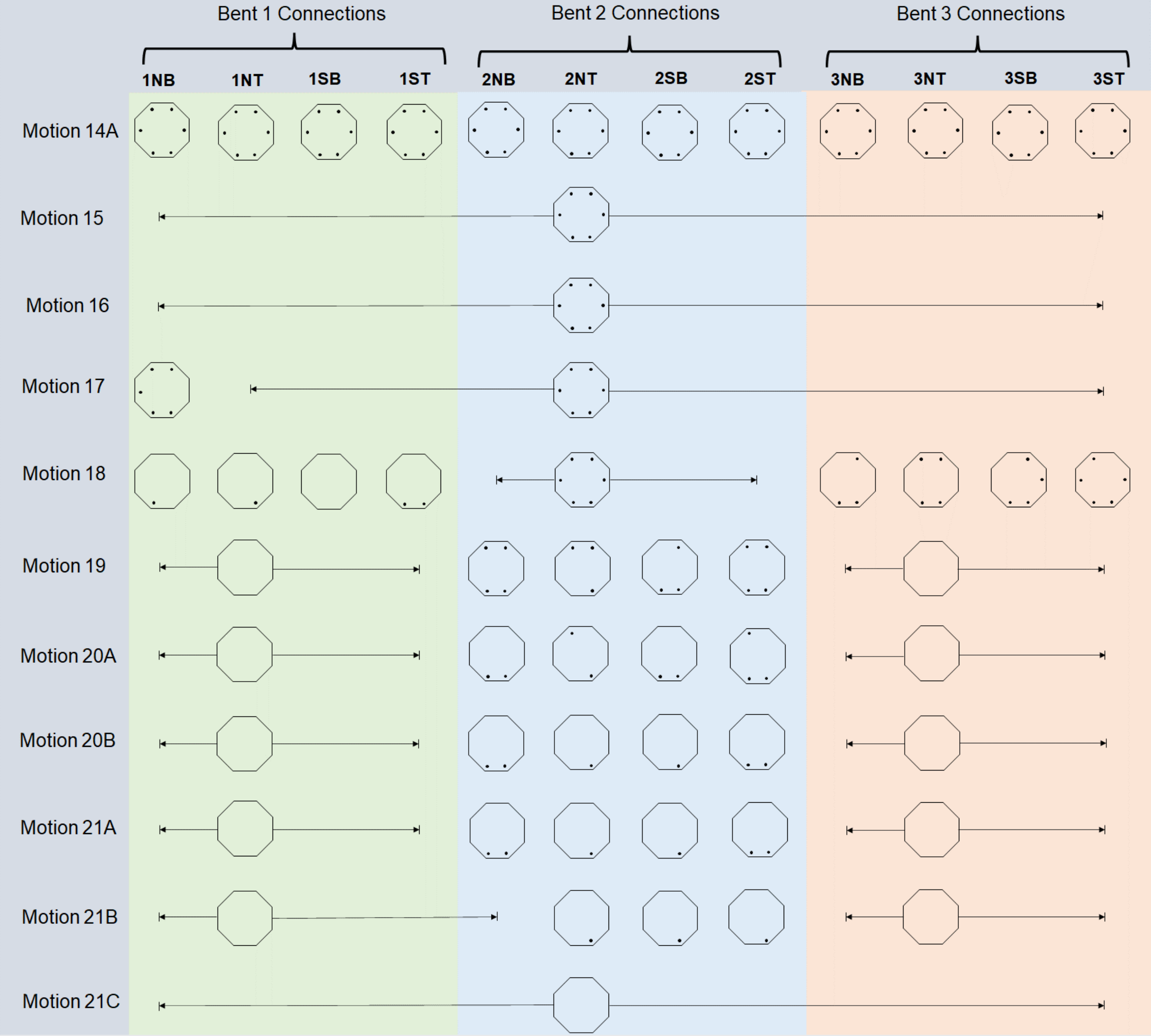


Strain Data

Earthquake Motions and Strain Data

Legend:





Seismic Testing:

- Three shake tables are used.
- 24 earthquake motions applied.
- Focus on 11 high-amplitude motions for fatigue damage.

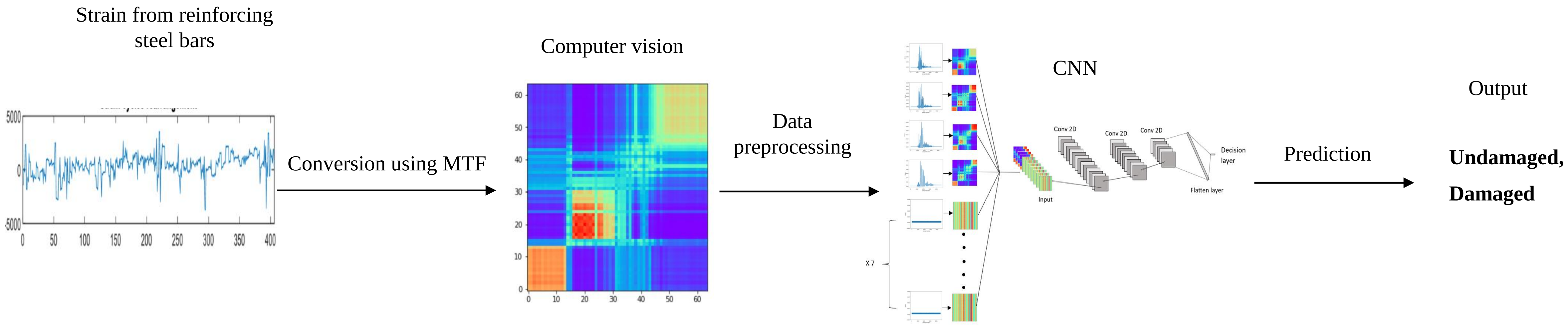
Strain Calculation:

- Utilized "Displacement Method" for strain estimation.
- Calculation based on rigid-body rocking assumptions.

Data Selection:

- Only strains from 11 high-amplitude motions are considered.

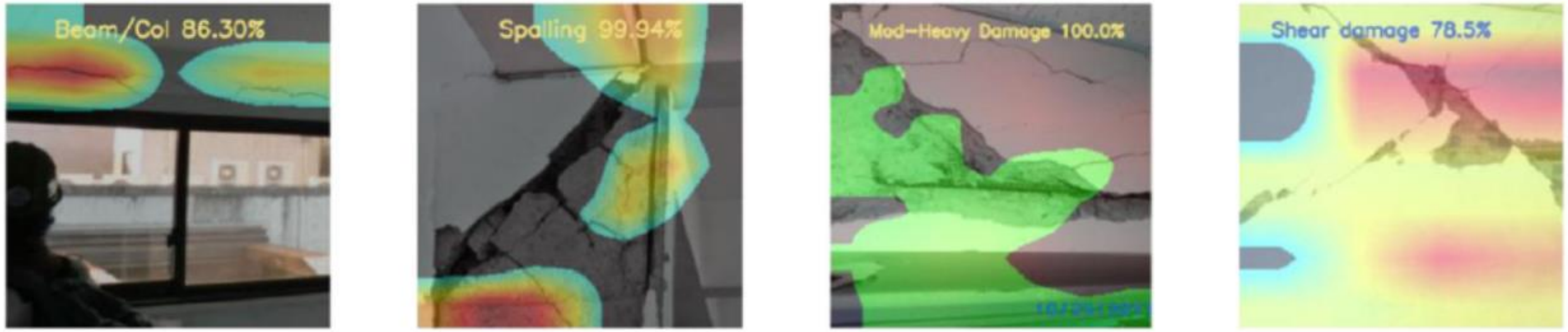
Detecting damage from strain using computer vision and machine learning algorithms



The use of only strain data instead of strain cycles in detecting damage to reinforcing bars. This helps in reducing the task of using the rainfall counting method.

Detecting damage from strain using computer vision and machine learning algorithms

Damage Detection from Images using Deep Learning and Transfer Learning

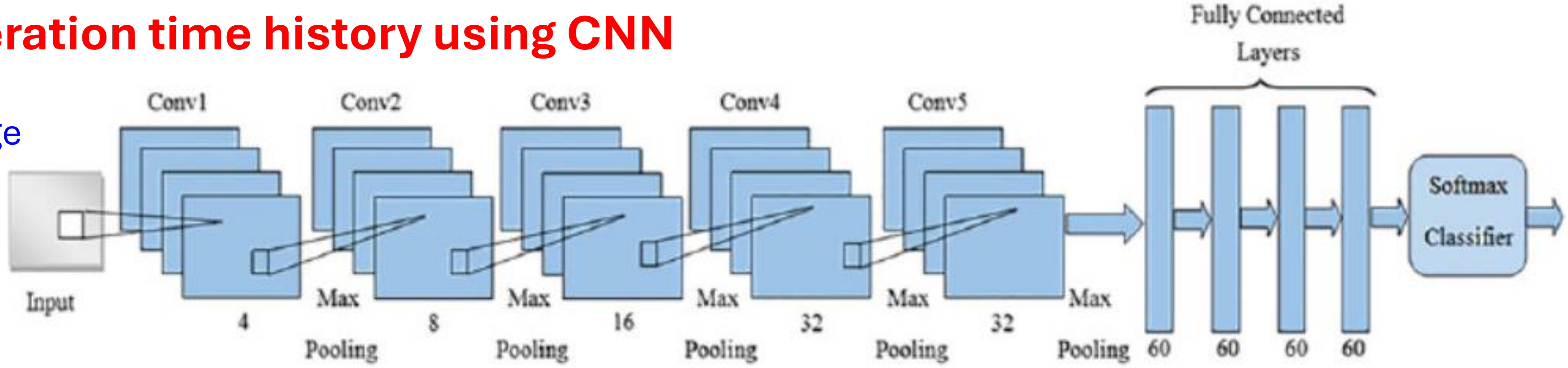


(a) Component type (b) Spalling condition (c) Damage level (d) Damage type

Gao, Y. and Mosalam, K.M. (2018), Deep Transfer Learning for Image-Based Structural Damage Recognition. Computer-Aided Civil and Infrastructure Engineering, 33: 748-768. https://doi.org/10.1111/mice.12363

Vibration Based Structural Condition Assessment using input images constructed from acceleration time history using CNN

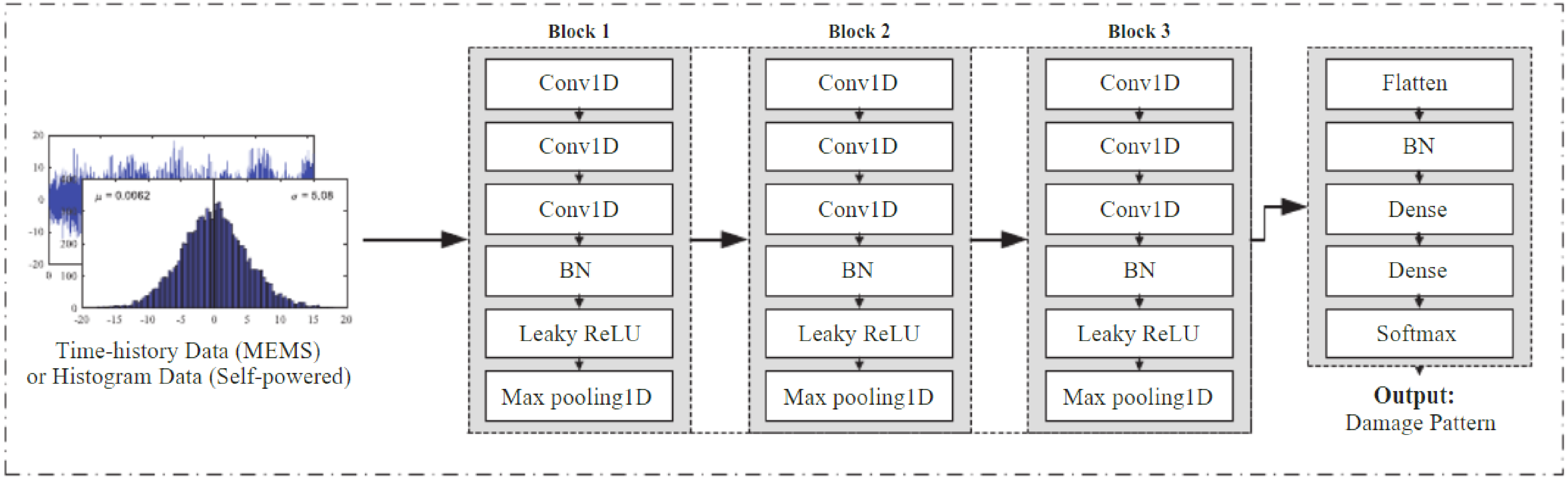
Reconstruct image matrix using acceleration time series data



Khodabandehlou, H., Pekcan, G., & Fadali, M. S. (2019). Vibration-based structural condition assessment using convolution neural networks. Structural Control and Health Monitoring, 26(2), e2308.

Detecting damage from strain using computer vision and machine learning algorithms

Converting time series to histogram data



Azimi, M., & Pekcan, G. (2020). Structural health monitoring using extremely compressed data through deep learning. Computer-Aided Civil and Infrastructure Engineering, 35(6), 597-614.

Constructing 2D- grid image from time series data and converting time-series data to histogram data ignores the **temporal effect** in the measured data (strain, displacement, acceleration)

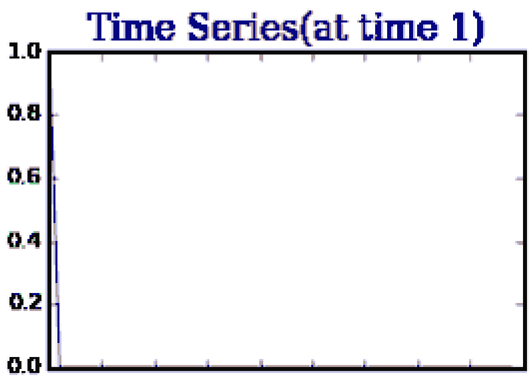
Detecting damage from strain using computer vision and machine learning algorithms

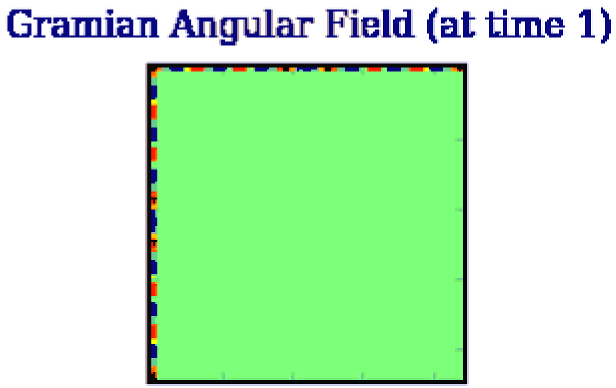
Data preprocessing

- Conversion of strain data to 2D images using Markov transition field
- After damage, noise strain data was created and it was also converted to a 2D image
- These images for all motions were stacked upon each other and used as input, as strain was not supposed to be added

MTF conversion:

$$M = \begin{bmatrix} w_{ij}|x_1\ q_i, x_1\ q_j & \cdots & w_{ij}|x_1\ q_i, x_n\ q_j \\ w_{ij}|x_2\ q_i, x_1\ q_j & \cdots & w_{ij}|x_2\ q_i, x_n\ q_j \\ w_{ij}|x_3\ q_i, x_1\ q_j & \cdots & w_{ij}|x_3\ q_i, x_n\ q_j \\ \vdots & \ddots & \vdots \\ w_{ij}|x_n\ q_i, x_1\ q_j & \cdots & w_{ij}|x_n\ q_i, x_n\ q_j \end{bmatrix}$$



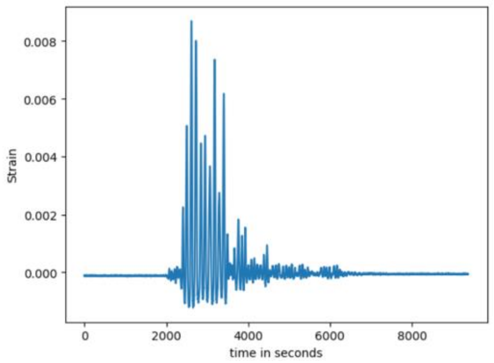


Detecting damage from strain using computer vision and machine learning algorithms

Data preprocessing

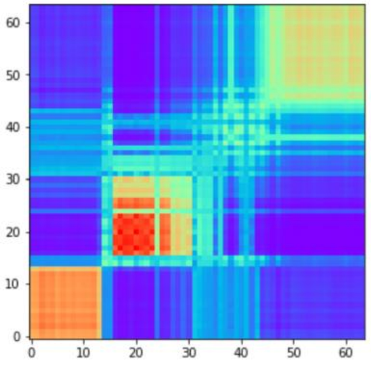
- Conversion of strain data to 2D images using Markov transition field
- After damage, noise strain data was created and it was also converted to a 2D image
- These images for all motions were stacked upon each other and used as input, as strain was not supposed to be added

Strain data

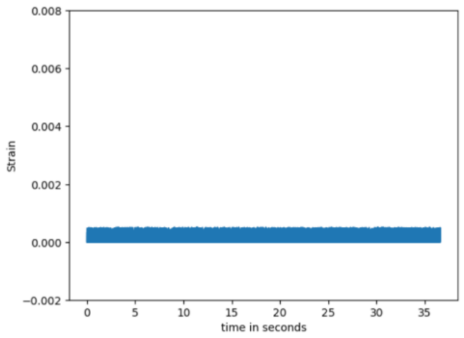


MTF

Image

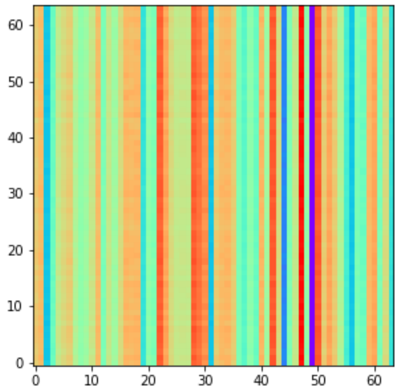


Noise Data data

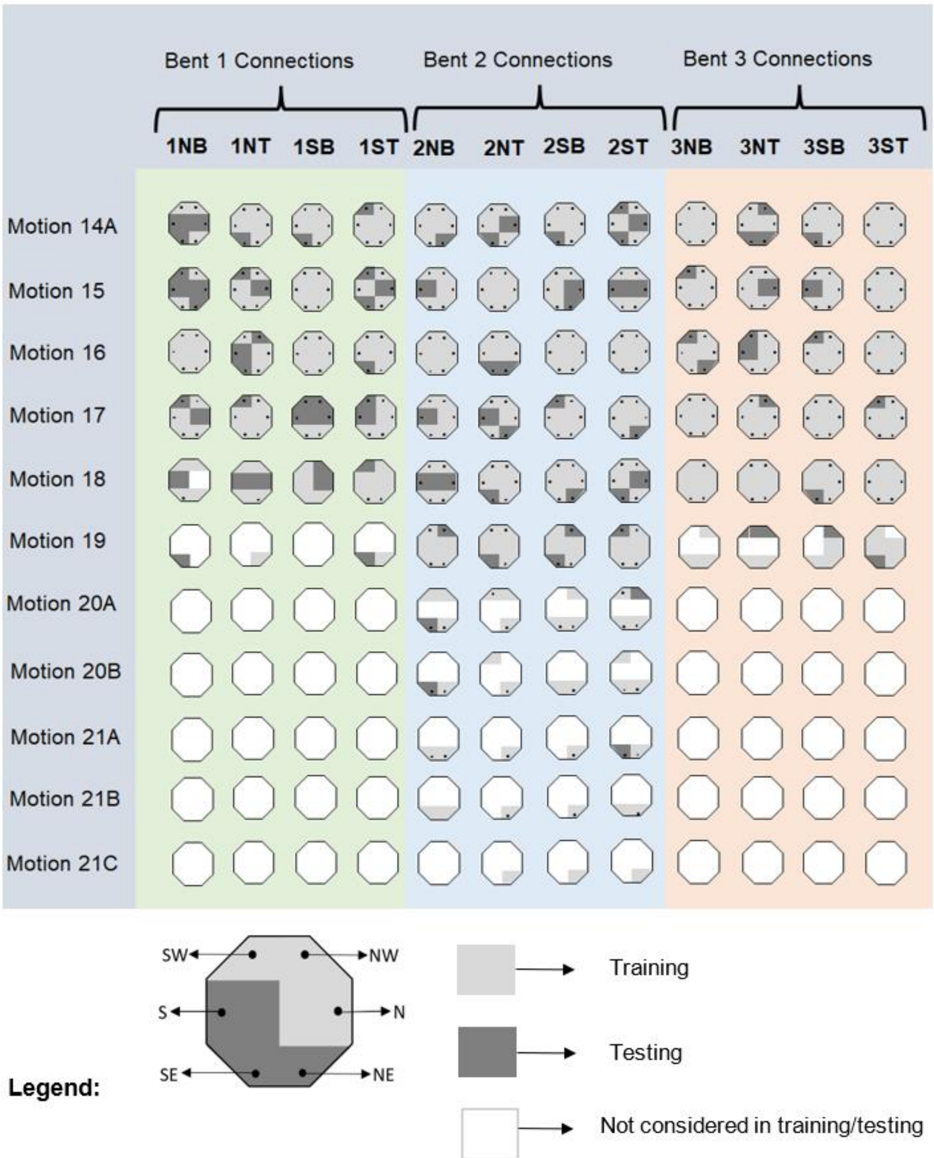


MTF

Image



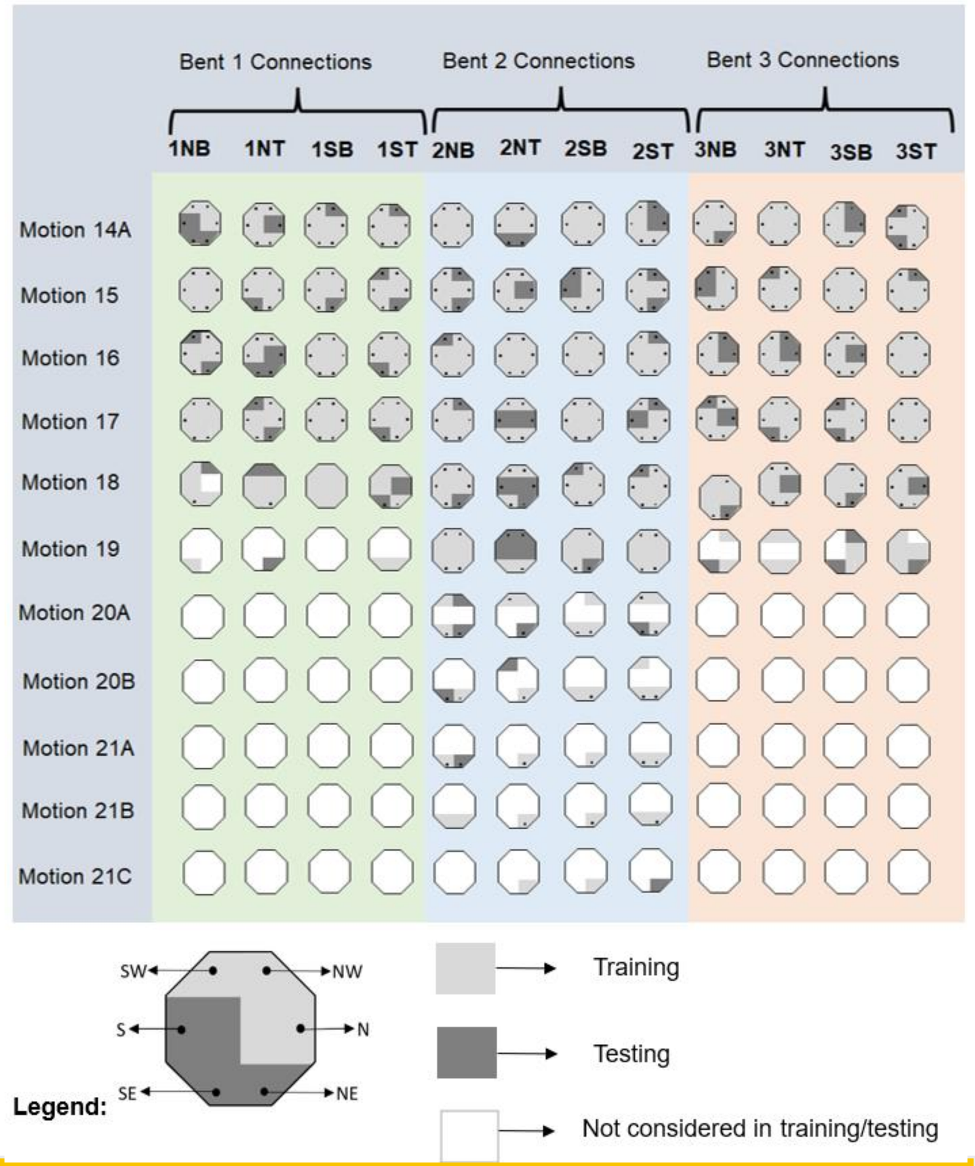
Detecting damage from strain using computer vision and machine learning algorithms



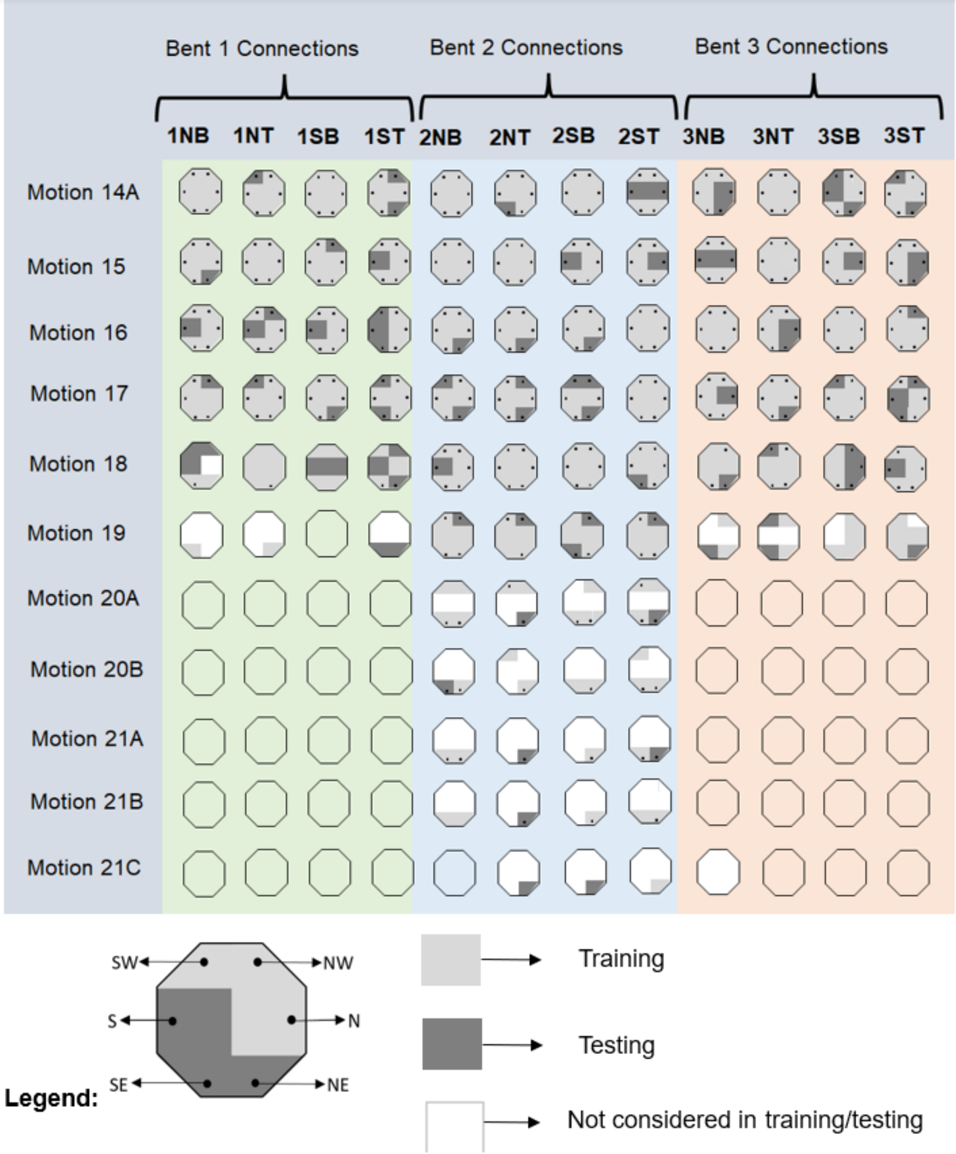
Scenario 1

Training verses Testing

Scenario 2



Detecting damage from strain using computer vision and machine learning algorithms



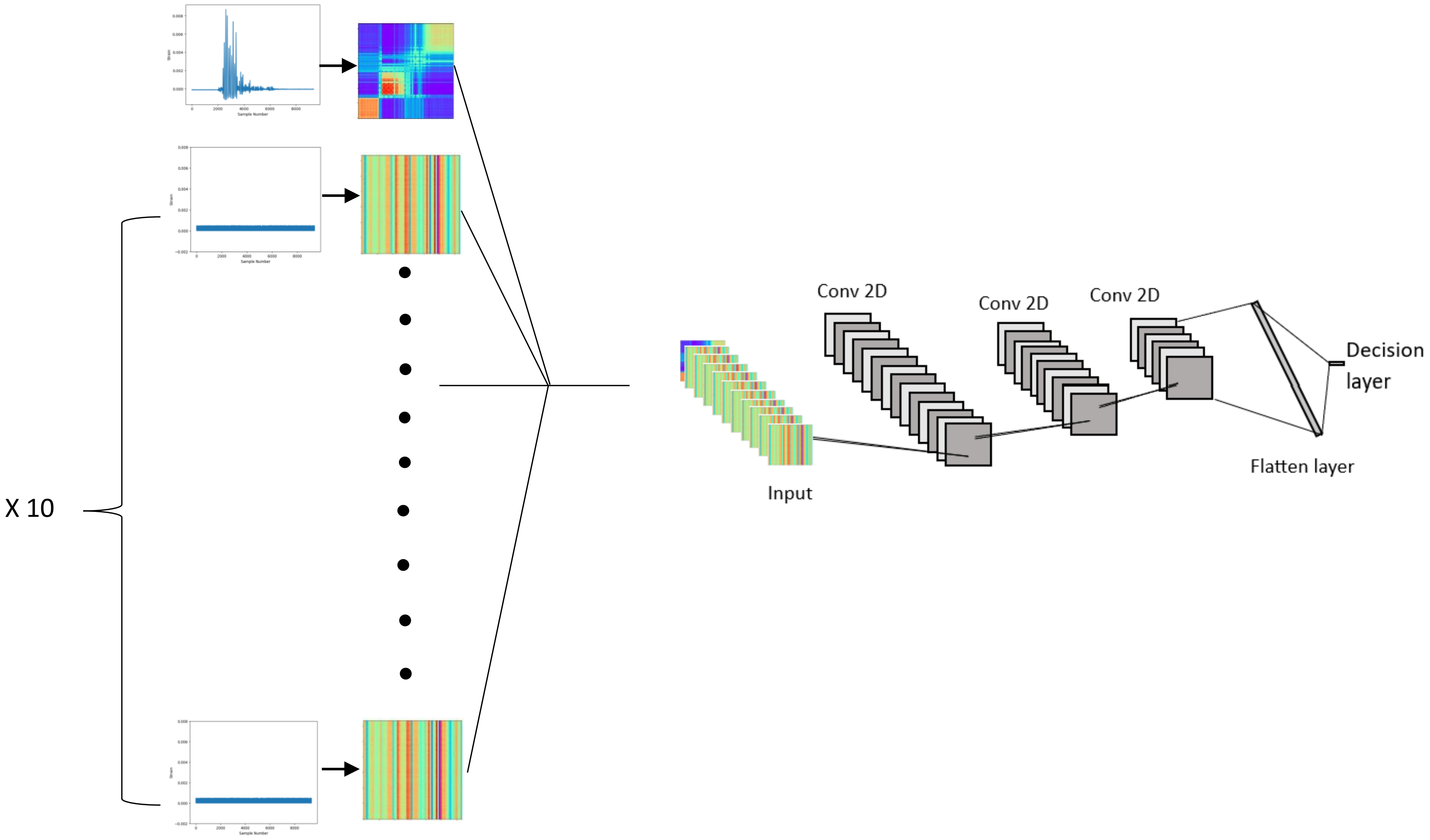
Scenario 3

Training verses Testing

Detecting damage from strain using computer vision and machine learning algorithms

CNN Architecture

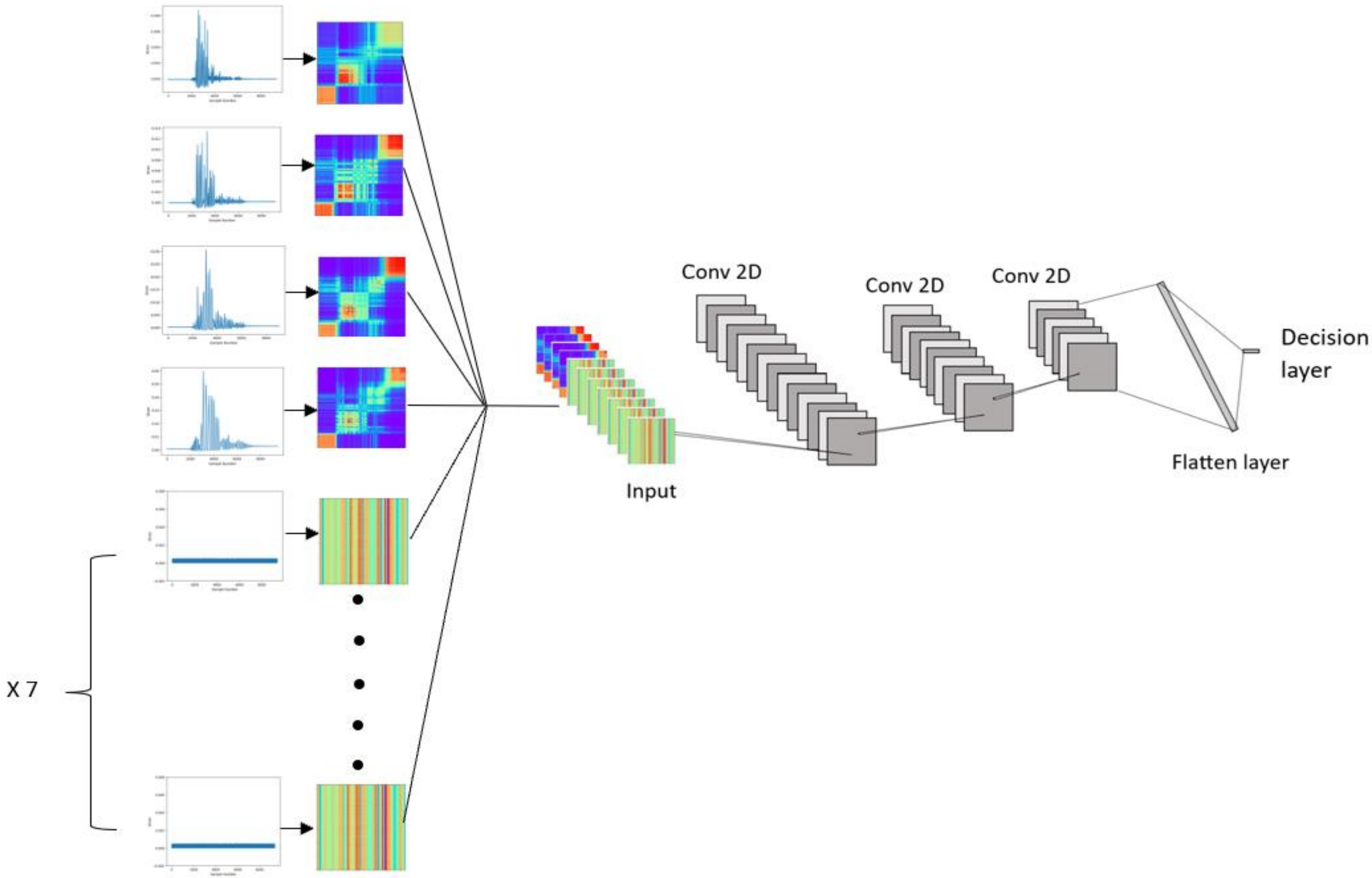
Undamaged Rebar



Detecting damage from strain using computer vision and machine learning algorithms

CNN Architecture

Damaged Rebar

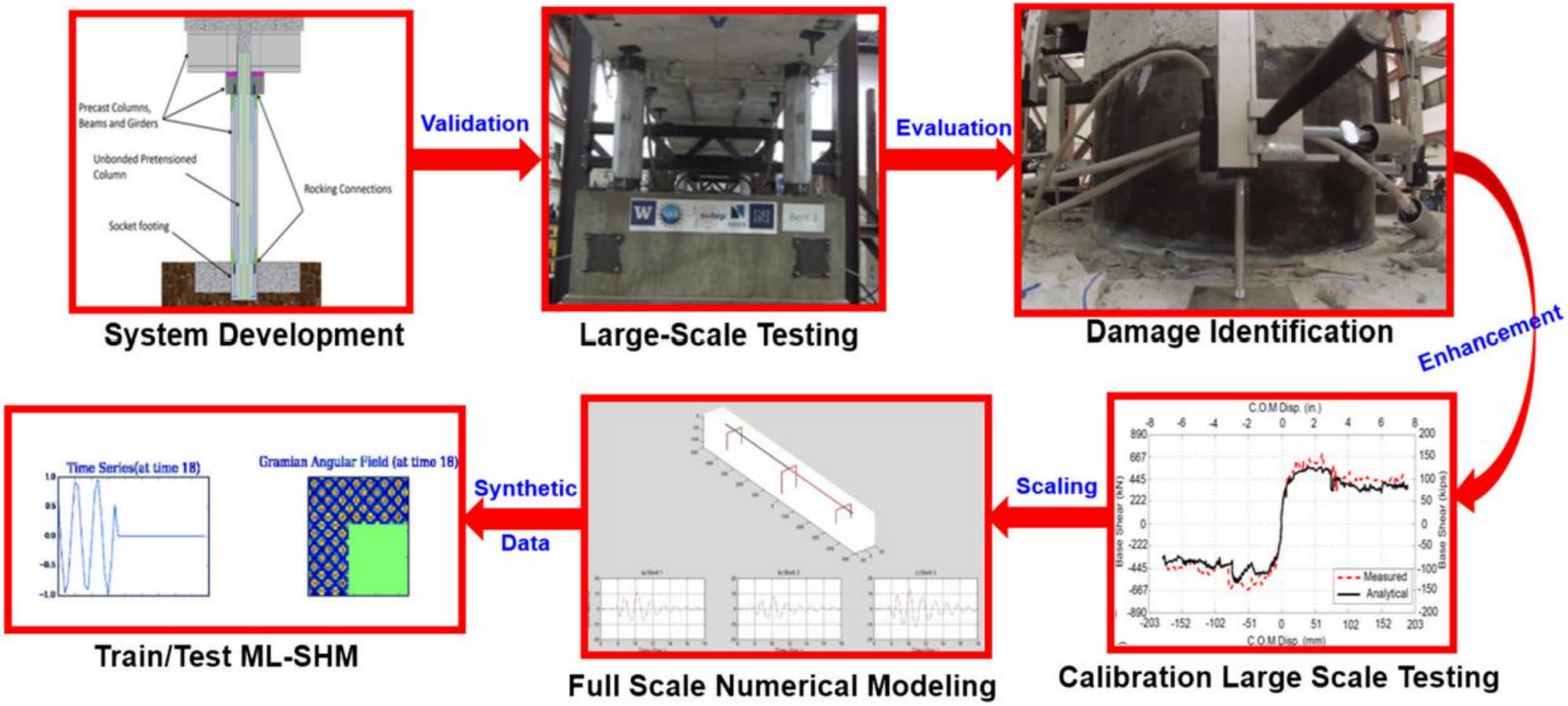


Results

		Training				Testing		
Scenario 1		No Damage	Damage	F1 Score		No Damage	Damage	F1 Score
	No Damage	294	0	1.0	No Damage	73	1	0.99
	Damage	0	57	1.0	Damage	1	14	0.93
	Accuracy			351	Accuracy			87
				100%				97.8%
Scenario 2		No Damage	Damage	F1 Score		No Damage	Damage	F1 Score
	No Damage	294	0	1.0	No Damage	73	1	0.98
	Damage	0	57	1.0	Damage	2	13	0.90
	Accuracy			351	Accuracy			86
				100%				96.7%
Scenario 3		No Damage	Damage	F1 Score		No Damage	Damage	F1 Score
	No Damage	294	0	1.0	No Damage	73	1	0.99
	Damage	0	57	1.0	Damage	1	14	0.94
	Accuracy			351	Accuracy			87
				100%				97.8%

Confusion Matrix

What is Next?



Precast Columns, Beams and Girders
Unbonded Pretensioned Column
Rocking Connections
Socket footing
System Development
Validation
Large-Scale Testing
Evaluation
Damage Identification
Enhancement
Calibration Large Scale Testing
Measured
Analytical
Scaling
Full Scale Numerical Modeling
Synthetic
Data
Time Series(at time 18)
Gramian Angular Field (at time 18)
Train/Test ML-SHM

Conclusions

1. The developed multi-channel input convolutional neural network model using encoded images from strain records showed excellent accuracy above 96% for all proposed scenarios.
2. The use of low noise strain time series data following the fracture of the reinforcing bar in the input channels was capable of balancing the input layer across the utilized data and enabled an efficient and robust CNN model.
3. The developed CNN model is simple and not overly complex, with three-layered CNN architecture with acceptable accuracy.
4. The developed process enabled, for the first time, the use of raw strain data to predict reinforcing bar fractures, which reduced the reliance on empirical equations for damage models and the use of cycle counting algorithms.
5. The use of CNNs can reduce the need for costly, time-consuming, and potentially ineffective traditional inspection techniques. CNNs can contribute to the development of more resilient and safer infrastructure by providing a more precise and efficient method of detecting and characterizing damage.

Acknowledgment

The presenter(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This project was funded by Rowan University and U.S. DOT through the Accelerated Bridge Construction University Transportation Center (ABC-UTC) at Florida International University (Grant Reference No. 69A3551747121)