KDD2020- Workshop

Real World Use Case:
Structural Health Monitoring (SHM)

Raghav Chalapathy
Nguyen Lu Dang Khoa
Sanjay Chawla

DATA 61 CSIRO
QCRI
معهد قطر لبحوث الحوسبة
Qatar Computing Research Institute
جامعة حمد بن خليفة
HAMAD BIN KHALIFA UNIVERSITY

Motivation

Why do we need SHM ?.

- Time-based maintenance
  - Preventative maintenance schedules
  - Too early or too late

Japan tunnel collapse 2012

Minneapolis bridge collapse 2007

Italy bridge collapse 2018

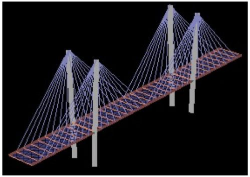
- Increase productivity and extend asset life.

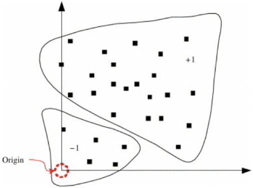
Levels of Damage Identification.

- Level 1 (Detection) : Is damage present?
- Level 2 (Localization) : Where is damage?
- Level 3 (Assessment) : How severe is damage?
- Level 4 (Prediction) : When will the structure fail?

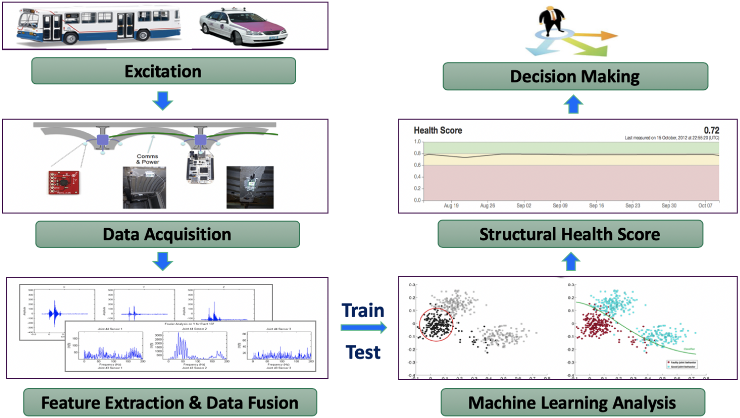
Damage Identification Techniques.

- Model-driven vs data-driven approach
  - Numerical model may not be available or accurate
  - Data-driven approach establishes a model from data.
- Our approach using deep models
  - Data corresponding to damage are often not available.
  - Only healthy data is available.
  - Challenge: Data drift.





SHM : Machine Learning Flowchart.



Case studies

System: Sydney Harbour Bridge

- Model-driven vs data-driven approach
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- Our approach using deep models
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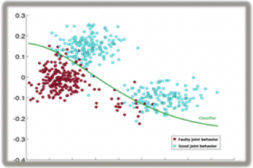
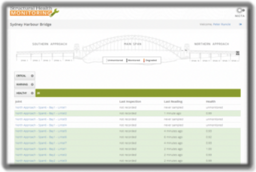
Steps : Structural Health Monitoring

- Numerical model may not be available or accurate
- Data-driven approach establishes a model from data.

Sensing

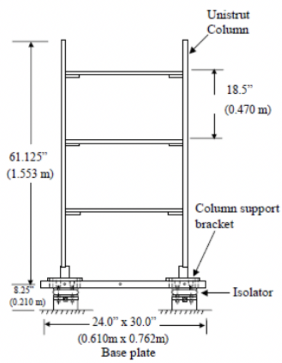


Data analytics



Continuous monitoring

Structures Monitored

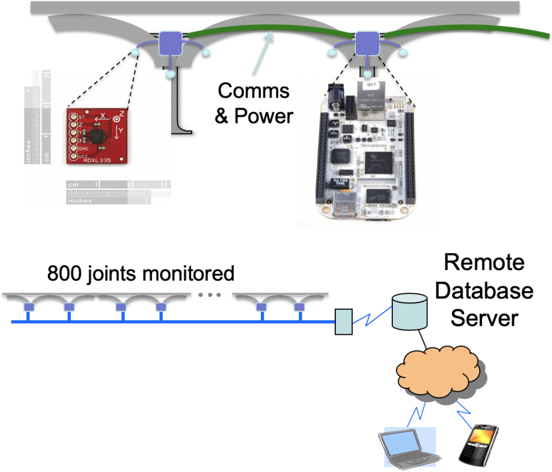


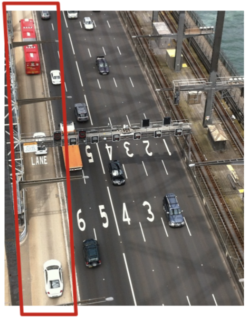
Sydney Harbour Bridge
- 3 sensors
- Sampling at 400Hz
- Damage in 1 location

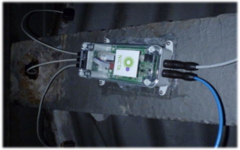
Lab-based bridge specimen
- 6 sensors
- Sampling at 500Hz
- Crack with different lengths

Lab-based building
- 24 sensors
- Sampling at 1600Hz
- Damage in 2 locations

System: SHM


Comms
& Power
ADXL335
800 joints monitored
Remote
Database
Server


LANE
6 5 4 3



Experiments

- Datasets: 2-Joints, BookShelf
- 900 for FFT features, 1800 for raw features
- Methods
  - One-Class Support Vector Machines (OCSVM)
  - Autoencoder (AE)
  - Robust Autoencoder (RAE)
  - One-Class Deep Support Vector Data Description (SVDD)
  - One-Class Neural Network (OCNN)

Results

(a) Two-Joints Decision Scores

	Two Joints		BookShelf	
	AUC	ACC	AUC	ACC
OCSVM	0.99	0.96	0.99	0.89
(OCNN)	0.95	0.90	0.99	0.95
One-Class SVDD	0.98	0.86	0.90	0.87
Soft One-Class SVDD	0.97	0.87	0.90	0.87
Robust Autoencoder (RAE)	0.98	0.97	**0.99**	**0.98**
Autoencoder (AE)	**0.98**	**0.98**	0.99	0.96

(b) Evaluation Metrics

Conclusion

- Deep learning-based techniques slightly better than OCSVM for Sydney Harbour Bridge dataset.
- Bookshelf data, the deep learning-based models outperform the traditional OCSVM model.
- Deep learning-based models as a good alternative on high-dimensional SHM data.