

Bridge HealthCare - Challenges and Prospects

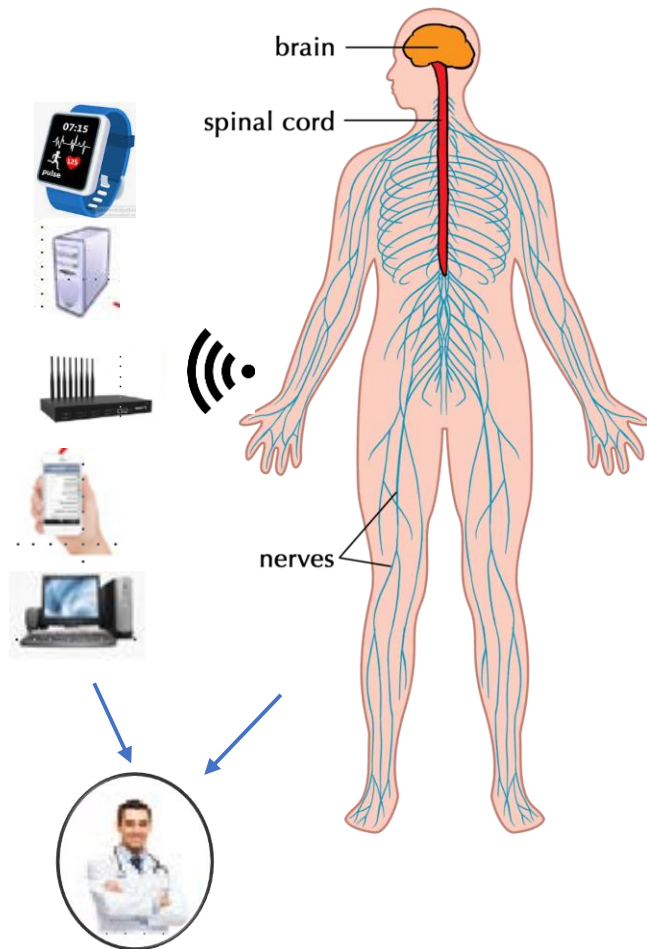
Professor Jianchun Li

Chair, Structural Dynamics

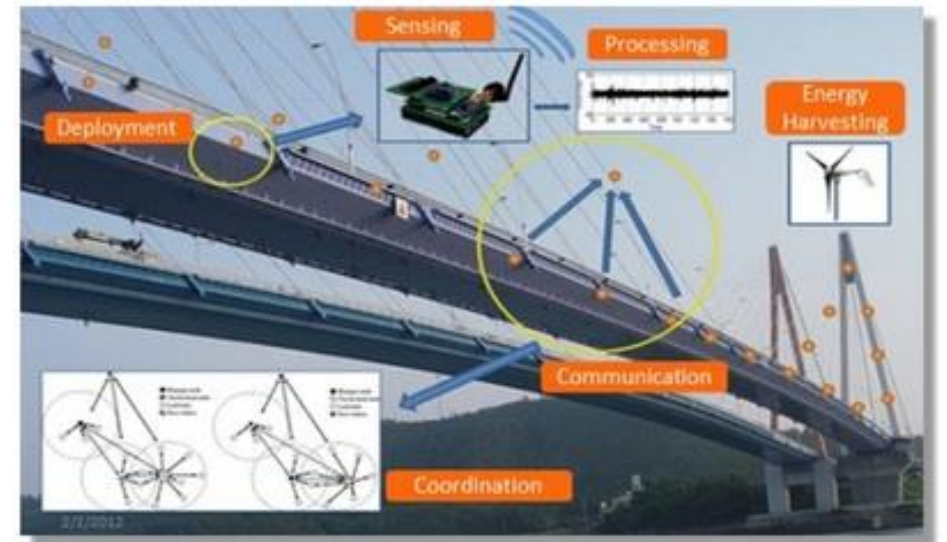
School of Civil and Environmental Engineering, UTS

Deputy President of ANSHM

HealthCare – Human vs Bridge



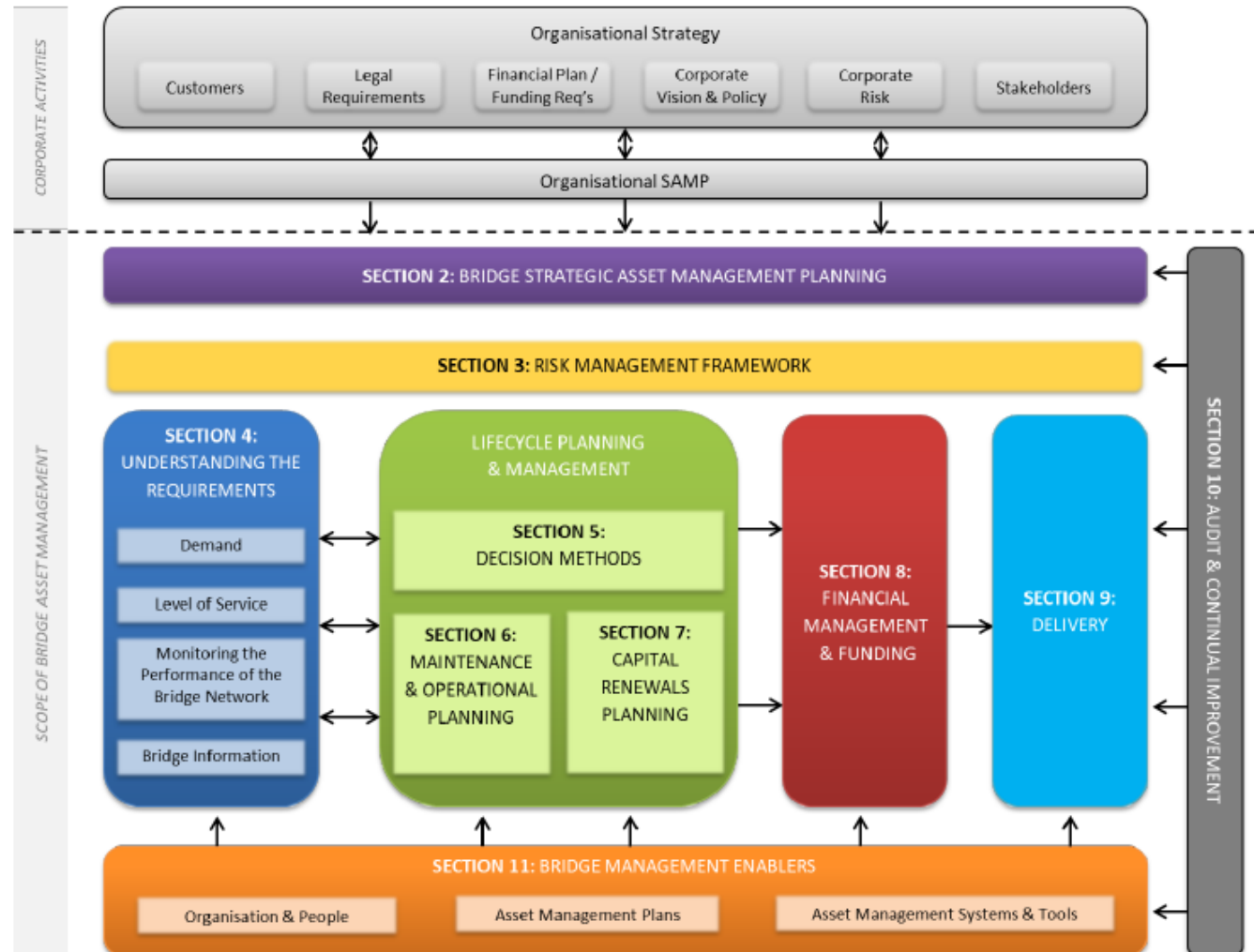
- Ageing
- Damage, injuries
- Sickness, deterioration
- Accidents
- Repair/replacement
- Cost, budget etc.



Challenges for Asset managers

Austrroads “Engineering Guideline to Bridge Asset Management”, January 2021

- defines best practice asset management for bridges, providing a transparent link between investment and outcomes
- presents a summary of the core asset management elements over the asset lifecycle



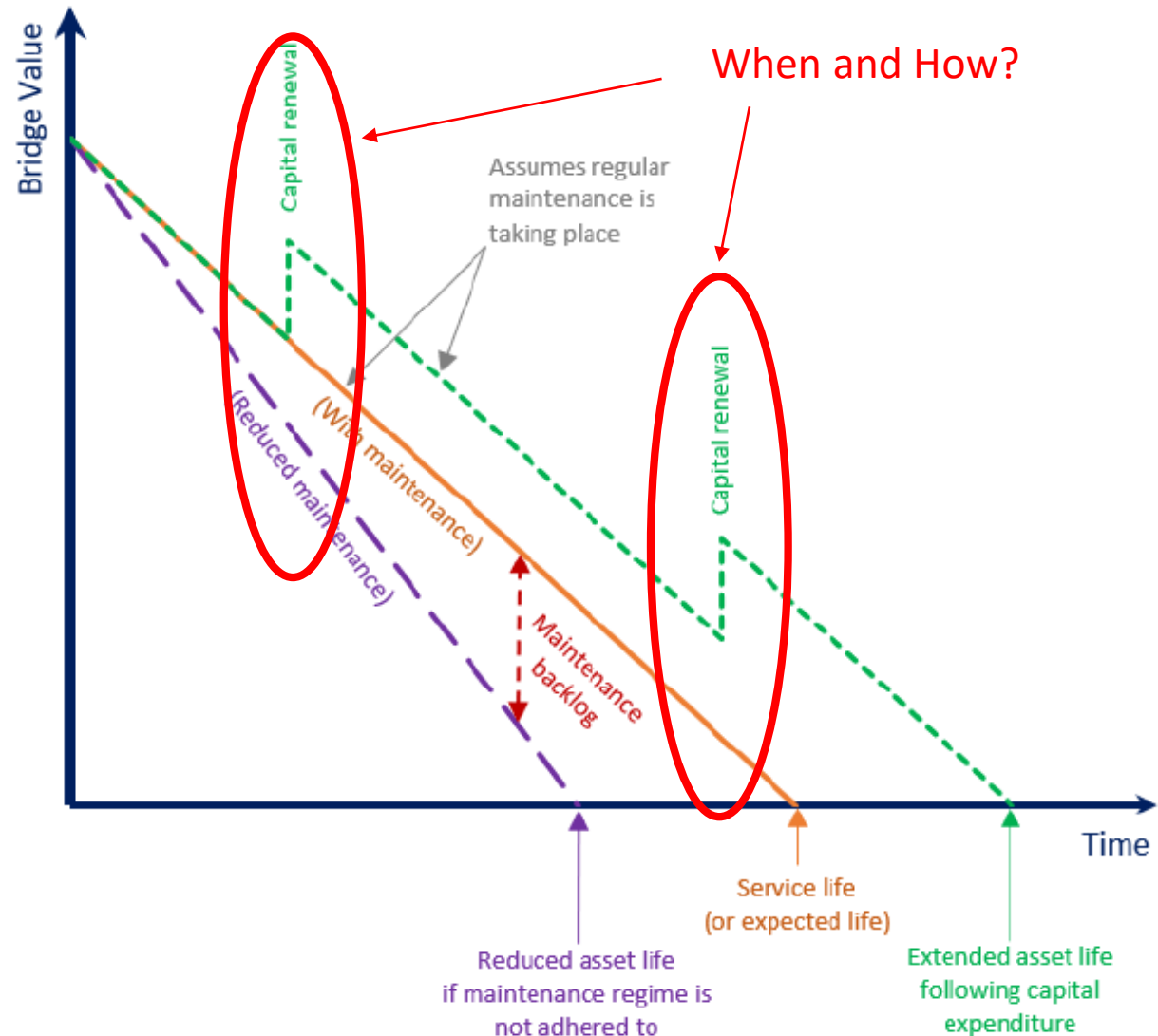
Overview of Bridge Asset Management Framework.

Challenges for Asset managers

The guideline is supposed to

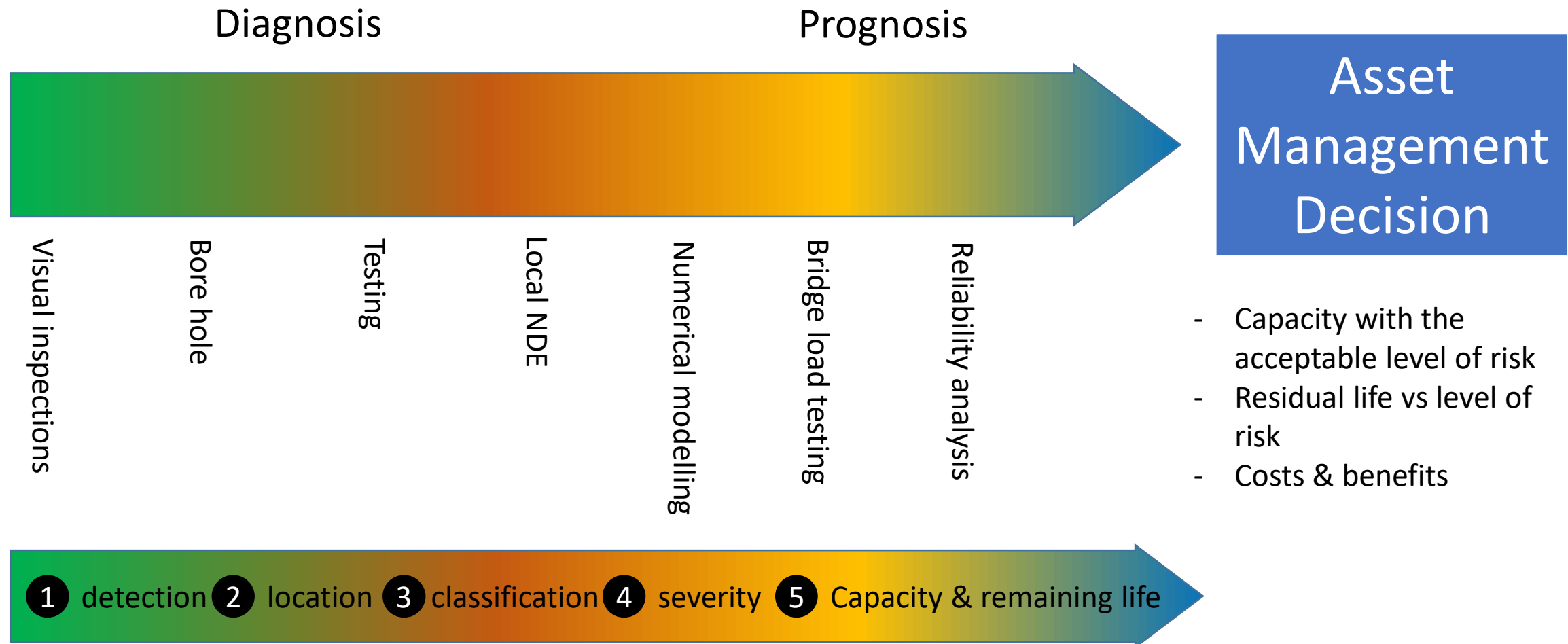
- Link investment and outcomes
- Promote the concept of formally measuring asset management performance to differentiate success from failure
- demonstrate results that illustrate accountability to customers and stakeholders
- identify gaps or needs that can justify funding

Questions are when & how?



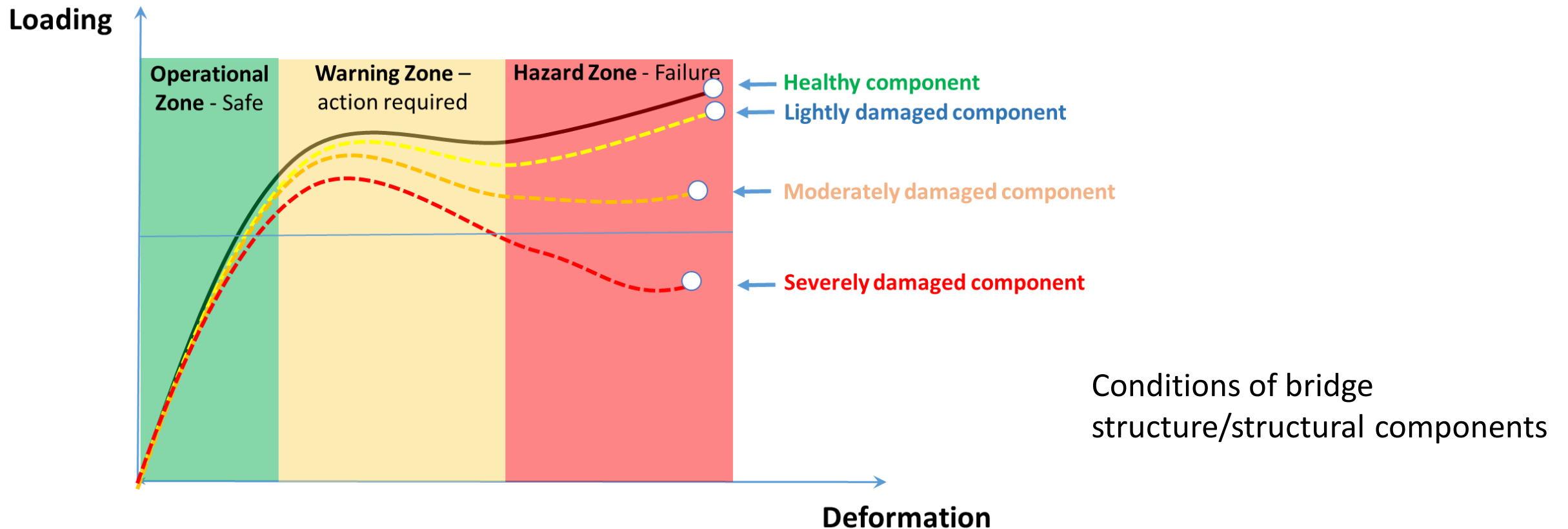
Principles of lifecycle activities that inform bridge assets management

Challenges for Asset Managers



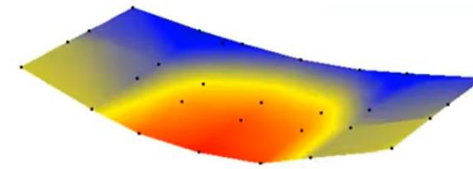
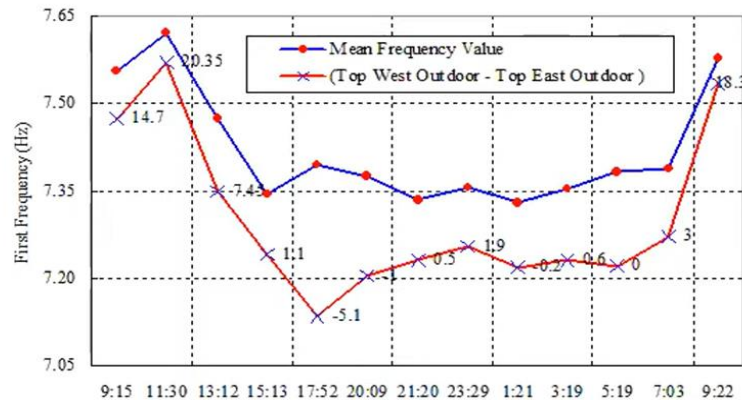
Challenges for Engineers/Researchers

- Enormous amount of data from monitoring
- Completely in-balanced data – few or none data from damaged cases

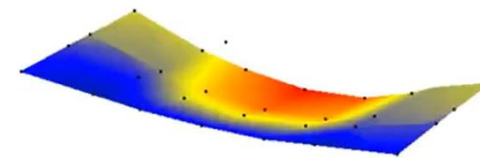


Challenges for Engineers/Researchers

- Damage detection is **NOT deterministic inverse problem**
- Operational and Environmental Variability (*an example from Farrar, Los Alamos National Laboratory, USA*)



First mode, 10 AM



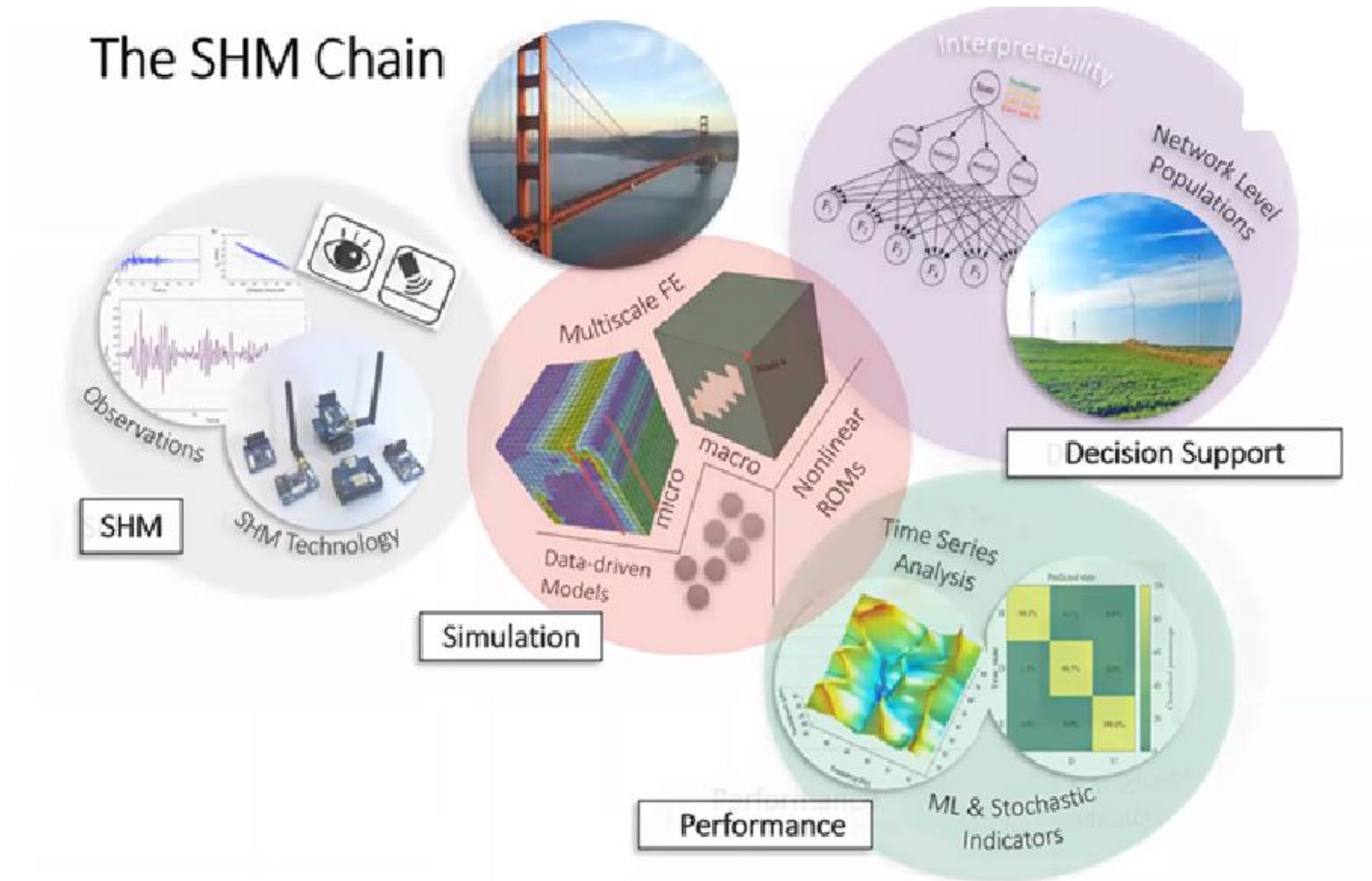
First mode, 5:30 PM

Technological advancement

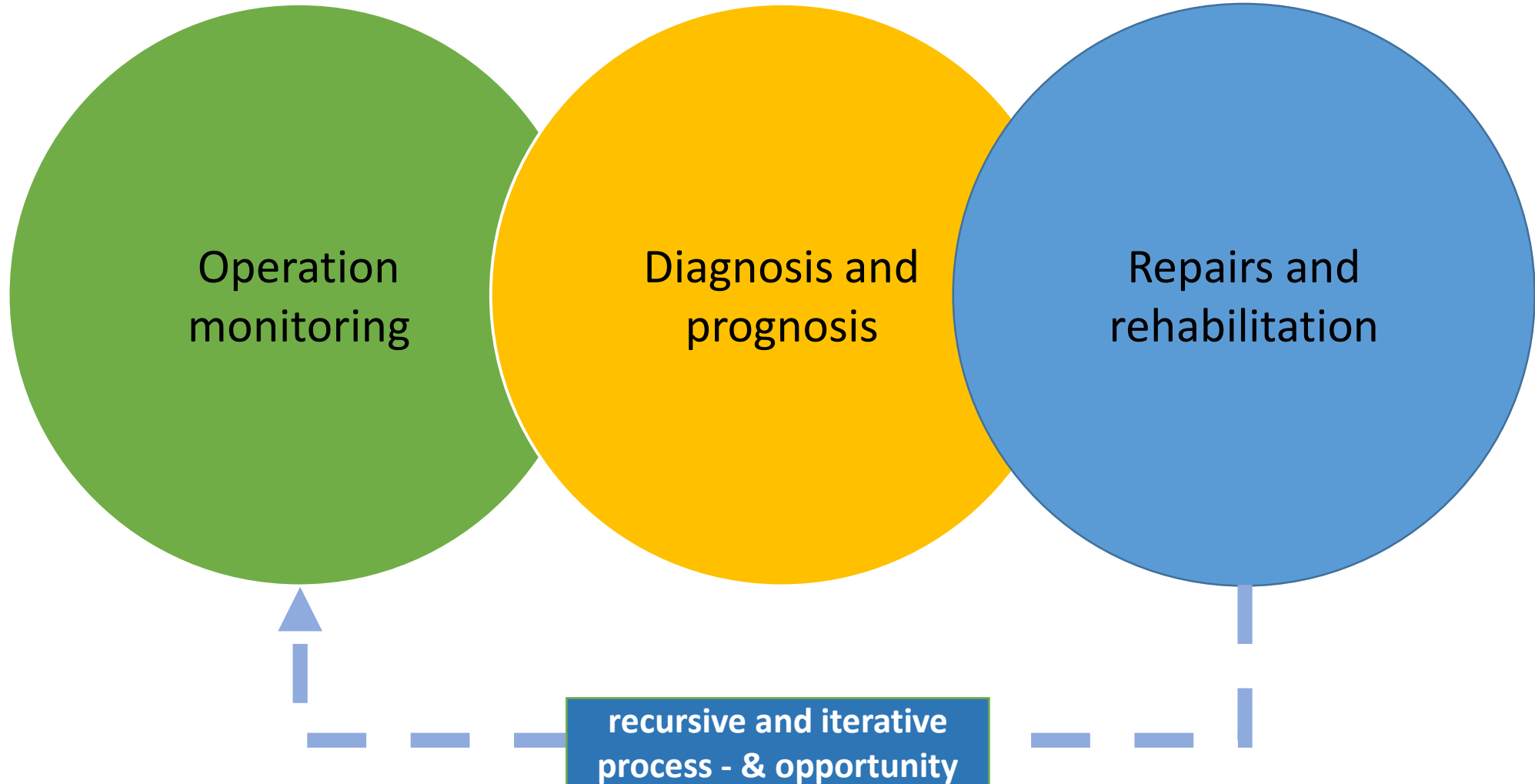
- Different perspectives on “Solutions” toward SHM problems
 - **Researchers:** define generic problem (often matched with methodology) to show it works
 - **Engineers:** define specific real problem and develop a solution for it
- **SHM dilemma**
 - **Assets owner** will not invest SHM technology until it works in real-world applications.
 - **Researchers** do not get opportunities to develop and demonstrate SHM technology.
- **Solution?**

Challenges for Engineers/Researchers

- SHM Chain
- Does SHM has RoI?
- Role of Data analytics and Machine Learning
- **Solution?**

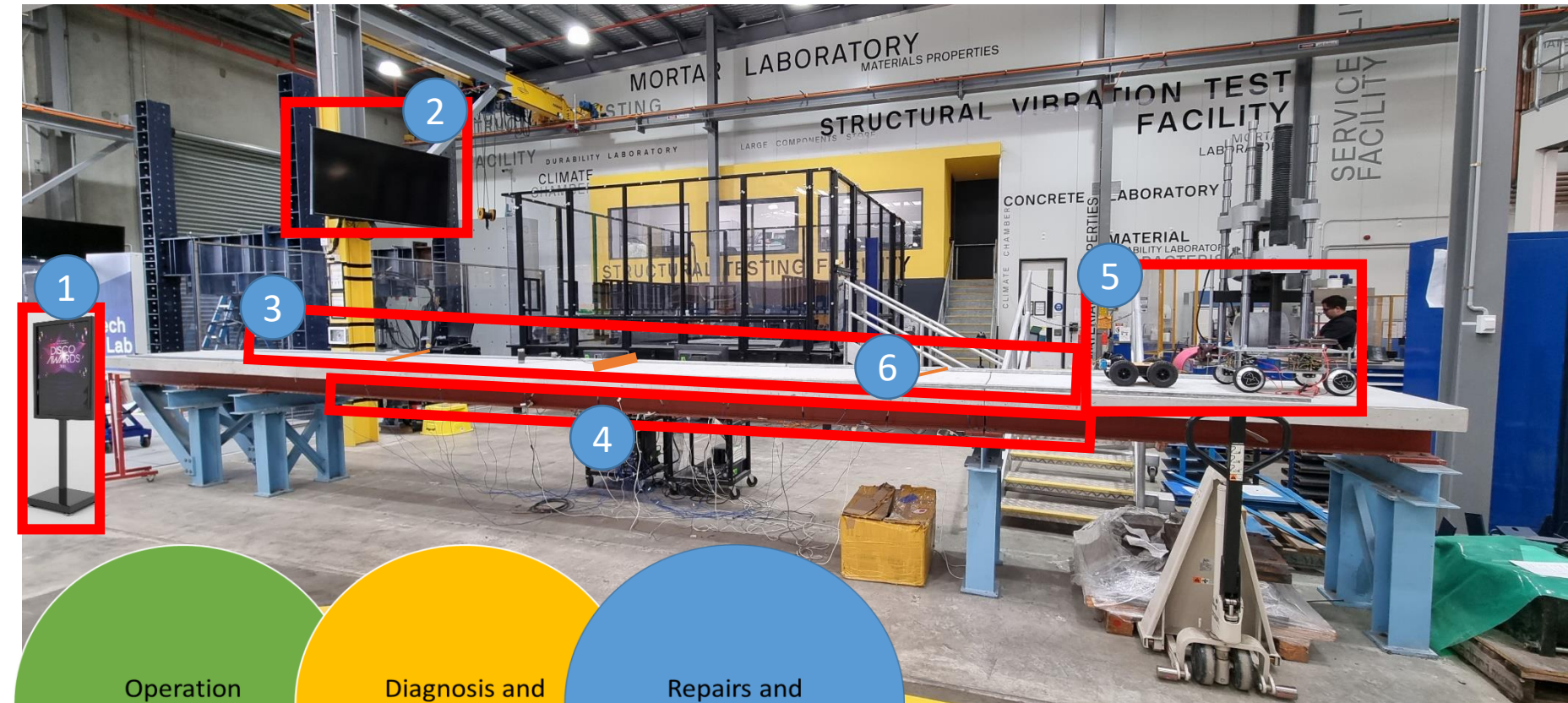


Bridge HealthCare framework

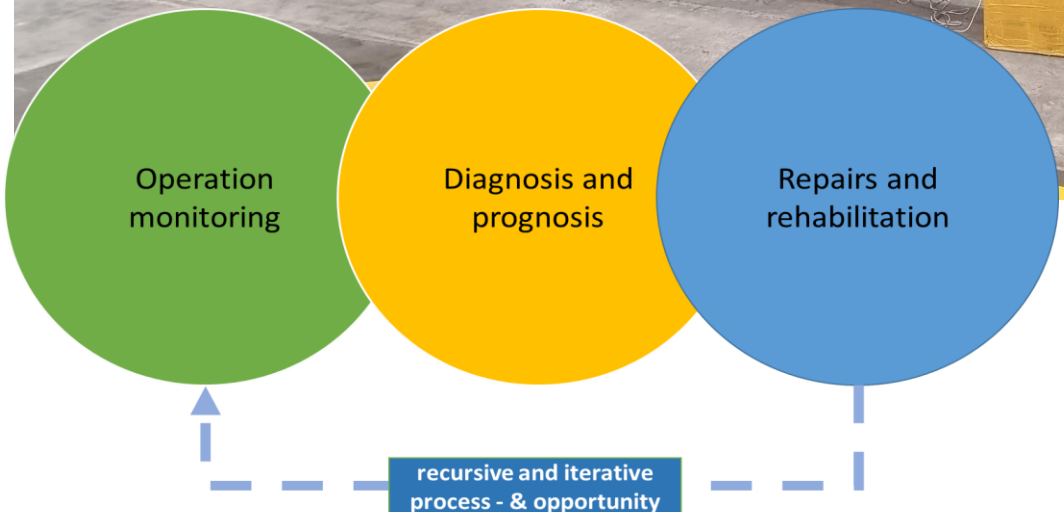


Bridge Healthcare Demo at UTS TechLab

- Integrated research into current practice



- Healthcare Design
- Healthcare procedure
 - **Benchmarking** with instrumented truck
 - **Monitoring** with crowdsource data
 - **Diagnosis & Prognosis** with instrumented truck and various tools + structural engineering knowledge/experience
 - **Risk & reliability assessments**
 - **Repair and rehabilitation**



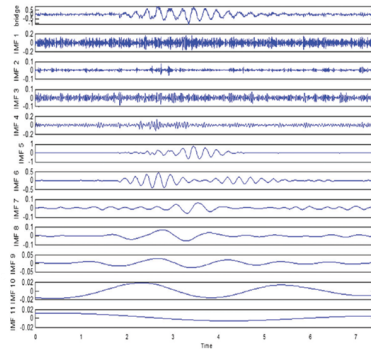
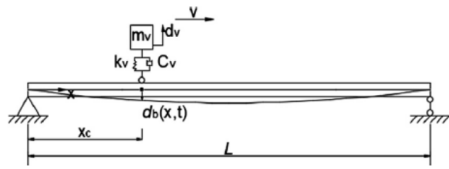
Examples of Bridge HealthCare research at UTS

1. Utilisation Vehicle-bridge interaction for structural damage detection - Saeid Talaei, PhD research project
2. Impact force localization and reconstruction - Bing Zhang, PhD research project
3. Structural damage detection for the semirigid joint spatial bridge with wireless measurements - Jiajia Hao, PhD research project
4. Implementing Transfer Learning for Damage Detection - Xutong Zhang, PhD research project
5. Advanced signal processing technique for extracting the time-varying feature of the VBI system - Mingzhe Gao, PhD research project
6. Development and Application of Self-sensing Concrete for Structure Health Monitoring - Dr Wengui LI, ARC future fellow
7. Bridge UAV crack detection with deep learning - Dr Yancheng LI, Senior Lecture
8. Intelligent Robotics for steel bridges and structures - Dist./Prof Dikai Liu, Robotics Institute, UTS

Utilisation Vehicle-bridge interaction for structural damage detection - Saeid Talaei, PhD research project

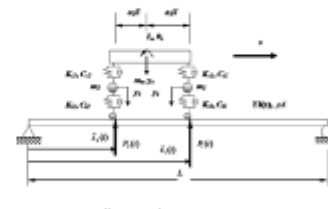
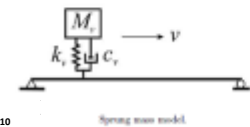
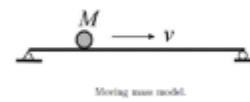
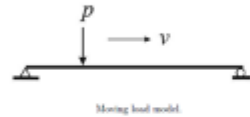
Vehicle-bridge interaction based structural damage detection

- Excitation force is close to the bridge operational condition
- Gives much more information compared to impact force
- Moving vehicle → less sensors
- More sensitive to local damage
- Time varying damage sensitive features



Vehicle Bridge Interaction Analysis Methods

- Vehicle Bridge Interaction Analysis can be done by 3 ways:
 - 1- modelling the passing vehicle as a moving load
 - 2- modelling the passing vehicle as a moving mass
 - 3- modelling the passing vehicle as a moving spring-mass system



$$\text{Bridge: } M_b \ddot{d}_b + C_b \dot{d}_b + K_b d_b = \phi(t) P_{\text{VBI}}(t)$$

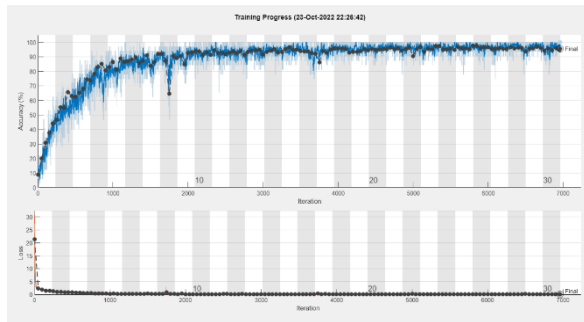
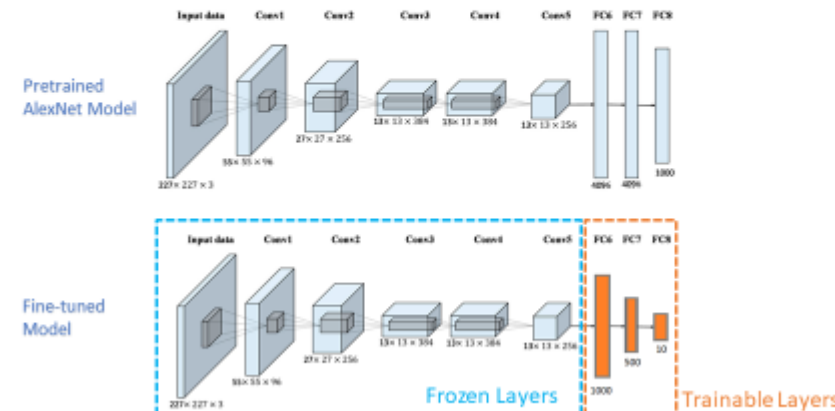
$$\text{Vehicle: } M_v \ddot{d}_v + C_v \dot{d}_v + K_v d_v = P_{\text{VBI}}(t)$$

$$\begin{bmatrix} M_b & m_v \phi \\ 0 & m_v \end{bmatrix} \begin{bmatrix} \ddot{d}_b \\ \ddot{d}_v \end{bmatrix} + \begin{bmatrix} C_b & 0 \\ -C_v \phi^T & C_v \end{bmatrix} \begin{bmatrix} \dot{d}_b \\ \dot{d}_v \end{bmatrix} + \begin{bmatrix} K_b & 0 \\ -K_v \phi^T & -C_v \phi^T \end{bmatrix} \begin{bmatrix} d_b \\ d_v \end{bmatrix} = \begin{bmatrix} \phi(t) P \\ 0 \end{bmatrix}$$

Coupled VBI model

Fine-tuning AlexNet Pretrained Network for Damage Detection

- Time-Frequency domain representation of the acceleration data corresponding to different damage scenarios are used to fine-tune the pretrained AlexNet model for damage localization



| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|----|----|----|----|----|----|----|----|----|----|----|----|
| 0 | 24 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 8 |
| 1 | 0 | 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 |
| 2 | 0 | 0 | 24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 23 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 24 | 0 | 3 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 23 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 23 | 3 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 1 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 16 |

Training loss and accuracy

Contusion matrix or classification results

Impact force localization and reconstruction

- Bing Zhang, PhD research project

❖ Low-rank transfer submatrix based group sparse regularization for impact force localization and reconstruction

Theoretical model

$M\ddot{x}(t) + C\dot{x}(t) + Kx(t) = LF(t)$

Expressed in the state space as,

$$\dot{z}(t) = Az(t) + BF(t)$$

where $z(t) = \begin{bmatrix} x(t) \\ \dot{x}(t) \end{bmatrix}$, $A = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix}$ and $B(t) = \begin{bmatrix} 0 \\ LM^{-1} \end{bmatrix}$

The measurement can be expressed as,

$$y(t) = Cz(t) + DF(t)$$

where $C = [-RM^{-1}K, -RM^{-1}C]$ and $D = RM^{-1}$

The continuous analytical solution,

$$y(t) = C\Phi(t)x(0) + C \int_0^t \Phi(t, \tau)BF(\tau)d\tau + DF(t)$$

where $\Phi(t) = \exp(At)$

Considering the zero initial conditions, the dynamic force is supposed to be an impulse signal,

$$F(t) = e_j \delta(t - \tau), \text{ with } e_j = [0, \dots, 0, 1, 0, \dots, 0]^T$$

The measured response at the j th point is

$$h_{jt}(t, \tau) = y_j(t) = C_j \int_0^t \Phi(t, \tau)B e_j \delta(\tau - \tau_1) d\tau + D e_j \delta(t - \tau_1)$$

Discrete expression based on general transfer matrix

Impact force identification based on transfer submatrix using one sensor

Group sparse regularization

$$\text{Minimize } \|H^P F^P - Y_1\|_2^2 + \lambda \sum_{i=1}^{nr} \|F_i^P\|_1$$

❖ Moving force identification via equivalent nodal force based on group weighted regularization

Group weighted regularization model

$$M\dot{X}(t) + C\dot{X}(t) + KX(t) = F(t)$$

$$F(t) = L(t)P(t)$$

$$L(t) = \begin{bmatrix} 0 & \dots & N_1(x(t)) & \dots & 0 \\ 0 & \dots & N_j(x(t)) & \dots & 0 \end{bmatrix}^T$$

One group weighted matrix W is introduced to eliminate the effect of zero entries,

$$F = WF$$

where $W = \text{diag}(w_{g1}, w_{g2}, \dots, w_{g(2nr-1)})$; $w_{g(2i-1)} = \text{diag}(1, 1, \dots, 1)$; $i = 1, 2, \dots, nr$;
 $w_{g(2i)} = \text{diag}(0, 0, \dots, 0)$; $i = 1, 2, \dots, nr$.

Then the L2-norm regularization could be expressed as,

$$\text{minimize } \|HWF - Y\|_2^2 + \lambda \|WF\|_2^2$$

Above equation has the analytic solution as,

$$F = ((HW)^T(HW) + \lambda I)^{-1}(HW)^T Y$$

Given the singular value decomposition

$$HW = U\Sigma V^T$$

where $U = [u_1, \dots, u_n]$; $V = [v_1, \dots, v_n]$; $\Sigma = \text{diag}(\sigma_1, \dots, \sigma_r)$.

The regularized solution can be expressed as

$$F = (V\Sigma U^T U \Sigma V^T + \lambda I)^{-1} V \Sigma U^T Y$$

with singular values,

$$F = \sum_{i=1}^r \frac{\sigma_i}{\sigma_i^2 + \lambda} u_i^T Y v_i$$

❖ Low-rank transfer submatrix based group sparse regularization for impact force localization and reconstruction

Experimental validation

Single impact force identification results

Double impact force identification results

The localization index results: (a) using L2-norm regularization; (b) using L1-norm regularization; (c) using L2,1-norm regularization;

Impact force time history reconstruction at real location results: (d) via L2-norm regularization; (e) via L1-norm regularization; (f) via L2,1-norm regularization.

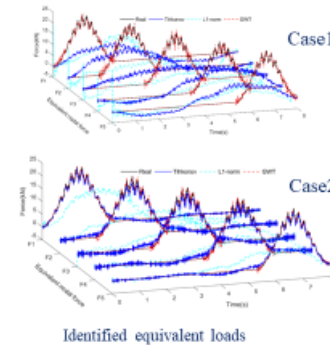
Identified equivalent loads

Identified moving force

❖ Moving force identification via equivalent nodal force based on group weighted regularization

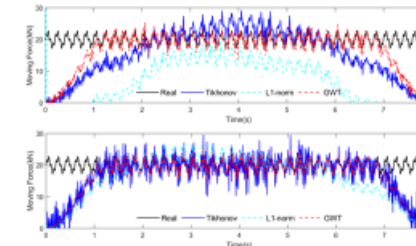
Numerical validation

□ The effect of the number of sensors



| Case | Positions of sensors | Positions of equivalent loads |
|------|----------------------------------|-------------------------------|
| 1 | L4, 2L4, 3L4 | L6, 2L6, 3L6, 4L6, 5L6 |
| 2 | L4, 2L6, 3L4, 4L6, 5L6 | L6, 2L6, 3L6, 4L6, 5L6 |
| 3 | L4, 2L6, 3L6, 4L6, 5L6, 6L4, 7L4 | L6, 2L6, 3L6, 4L6, 5L6 |

| Case | GRE (%) | | | MRE (%) | | |
|-------|----------|---------|-------|----------|---------|------|
| | Tikhonov | L1-norm | GWT | Tikhonov | L1-norm | GWT |
| Case1 | 34.64 | 74.69 | 20.16 | 21.57 | 70.17 | 5.03 |
| Case2 | 24.61 | 31.65 | 20.78 | 12.91 | 17.82 | 5.04 |
| Case3 | 24.77 | 31.37 | 19.97 | 12.73 | 17.44 | 3.94 |



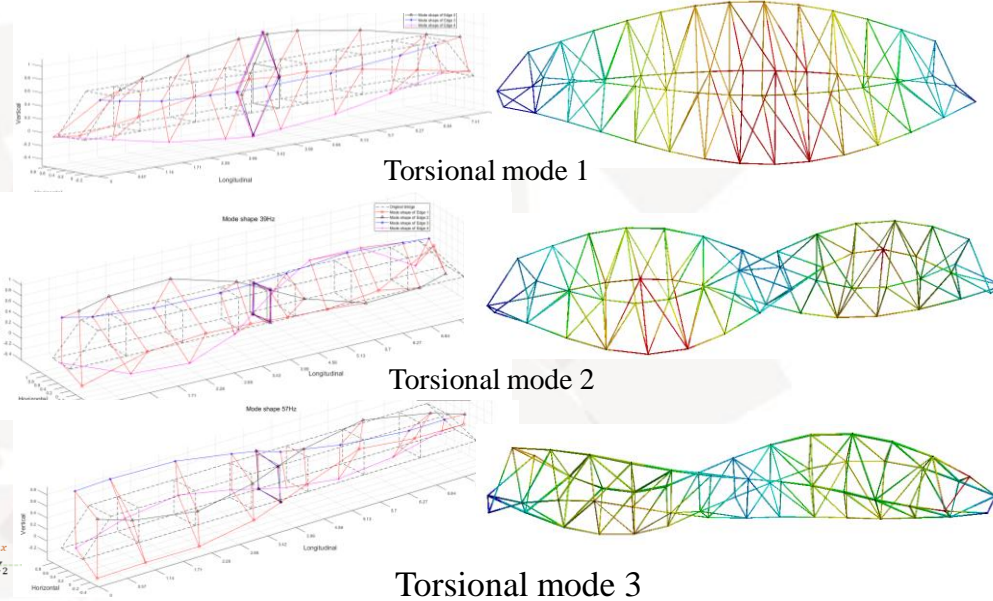
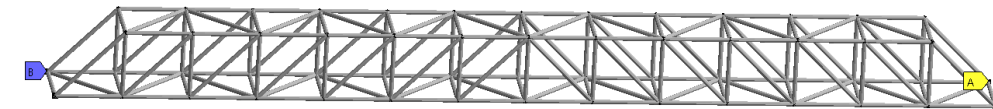
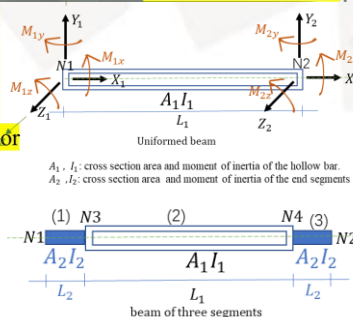
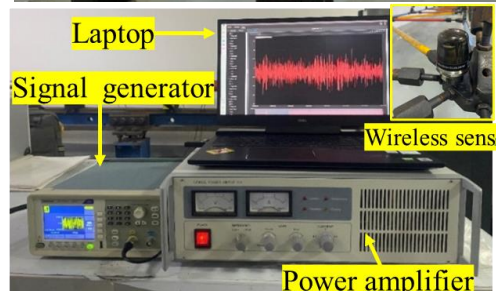
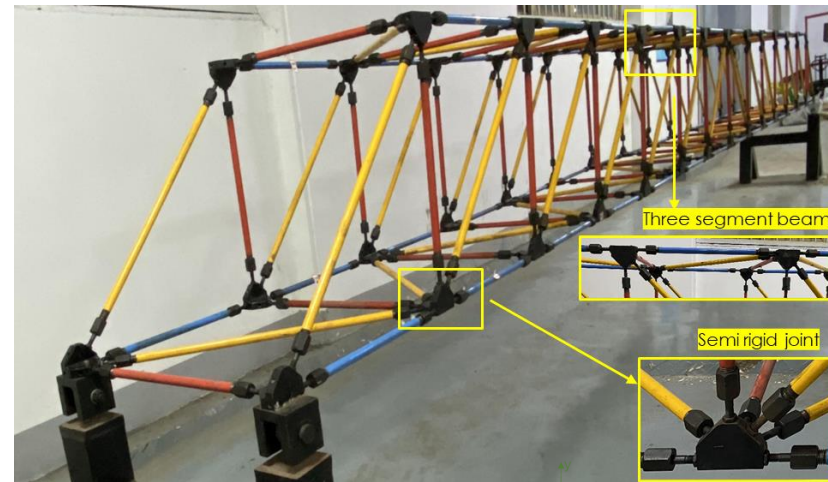
Identified moving force

Structural damage detection for the semirigid joint spatial bridge with wireless measurements

- Jiajia Hao, PhD research project

semi rigid joint model of nonuniform cross section element is developed considering both element and joint stiffness.

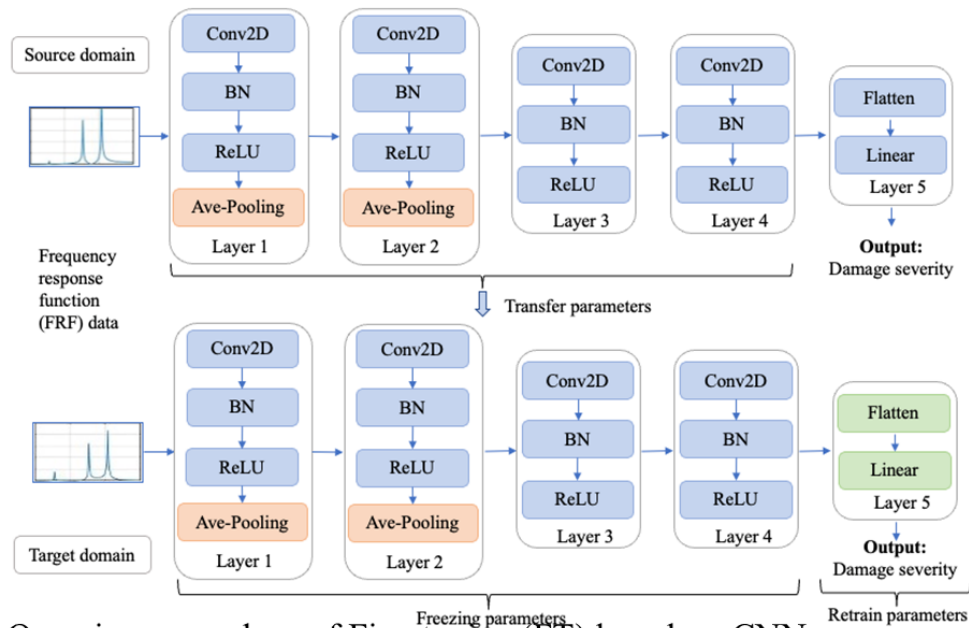
Joints are usually simulated as rigid while they are semi rigid. Failing to consider semi rigid joints **leads to low damage identification results.**



For the damage detection of all damage scenarios, semi rigid joint model outperform the rigid model. **Without joint stiffness updating, damage detection accuracy of spatial structures compromise.**

Implementing Transfer Learning for Damage Detection

- Xutong Zhang, PhD research project



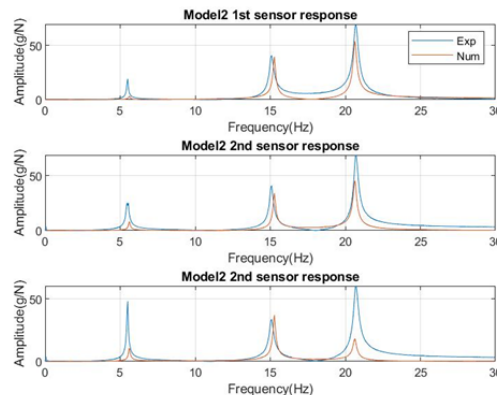
Case study: Lumped mass model, single damage case study: sample numbers in each damage scenario for each domain.

| | Training | | Testing | | | |
|------------------------|--------------------------|------------|---------------|------------------|------------|---------------|
| | Source domain | Undamage d | Single damage | Target domain | Undamage d | Single damage |
| Source domain 1 | Numerical (CNN) | D0 243 | D1 243 | Experimen tal | D0 108 | 10D2 108 |
| D2 243 | | | 20D2 108 | | | |
| D3 243 | | | | | | |
| Target domain 1 | Experimen tal (FT) | D0 108 | 10D2 108 | Experimen tal | D0 54 | 10D2 54 |
| 20D2 108 | | | 20D2 54 | | | |
| | | | | | | |

Note: D0 is the intact structure; D1 is the 0-30% damage on the first floor; D2 is the 0-30% damage on the second floor; D3 is the 0-30% damage on the third floor; 10D2 is 10% on the second floor; 20D2 is 20% damage on the second floor.

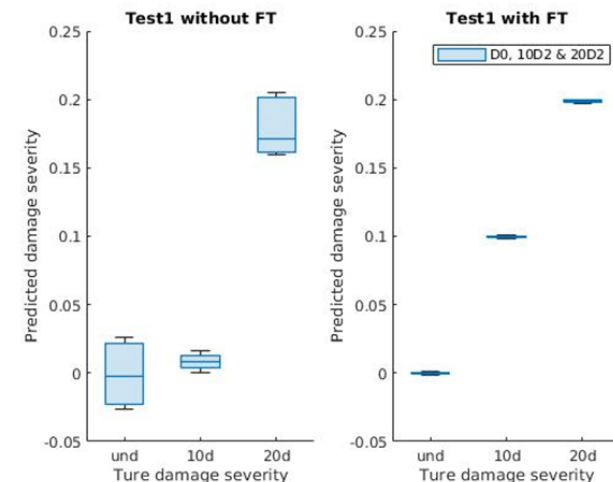
Overview procedure of Fine tuning (FT) based on CNN

Data preparation



Results

- High accuracy of the overall performance for predicting the damage severity across different domains.



Advanced signal processing technique for extracting the time-varying feature of the VBI system

- Mingzhe Gao, PhD research project

The proposal of this project is to develop a novel machine learning and signal processing based algorithm for bridge condition assessment. The detail objectives are as follows

- **Vehicle-bridge model** Use matlab to make finite element modal to construct model shown as Figure 1

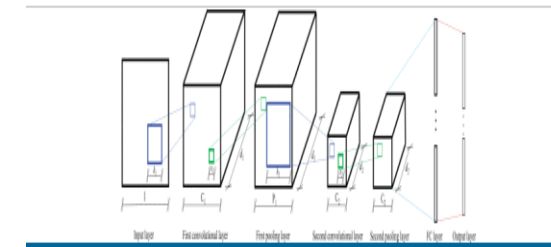


Figure 1 vehicle model

- **Synchroextracting Transform (SET):** As the same as SST then calculate the estimation IF

The final step is energy extraction :

$$Te(t, \omega) = G_e(t, \omega) \cdot \delta(\omega - \omega_0(t, \omega))$$
$$\delta(\omega - \omega_0(t, \omega)) = \begin{cases} 1, & \omega = \omega_0 \\ 0, & \omega \neq \omega_0 \end{cases}$$

- **Two stream CNN :** 2D-CNN takes **SET time-frequency map as input**, and 1D-CNN takes **FFT spectral signal as input**, and performs convolution layer and pooling respectively

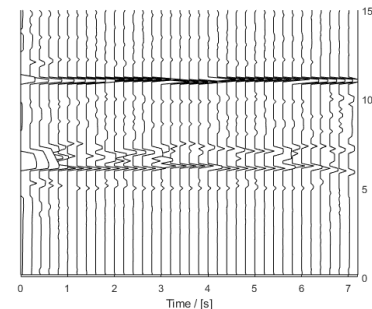


Figure 2 SET of acceleration of vehicle based on damage bridge

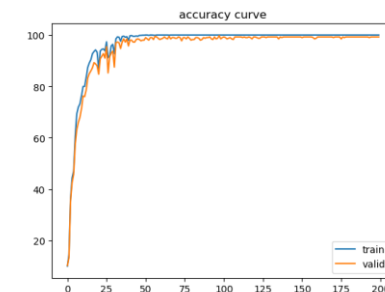
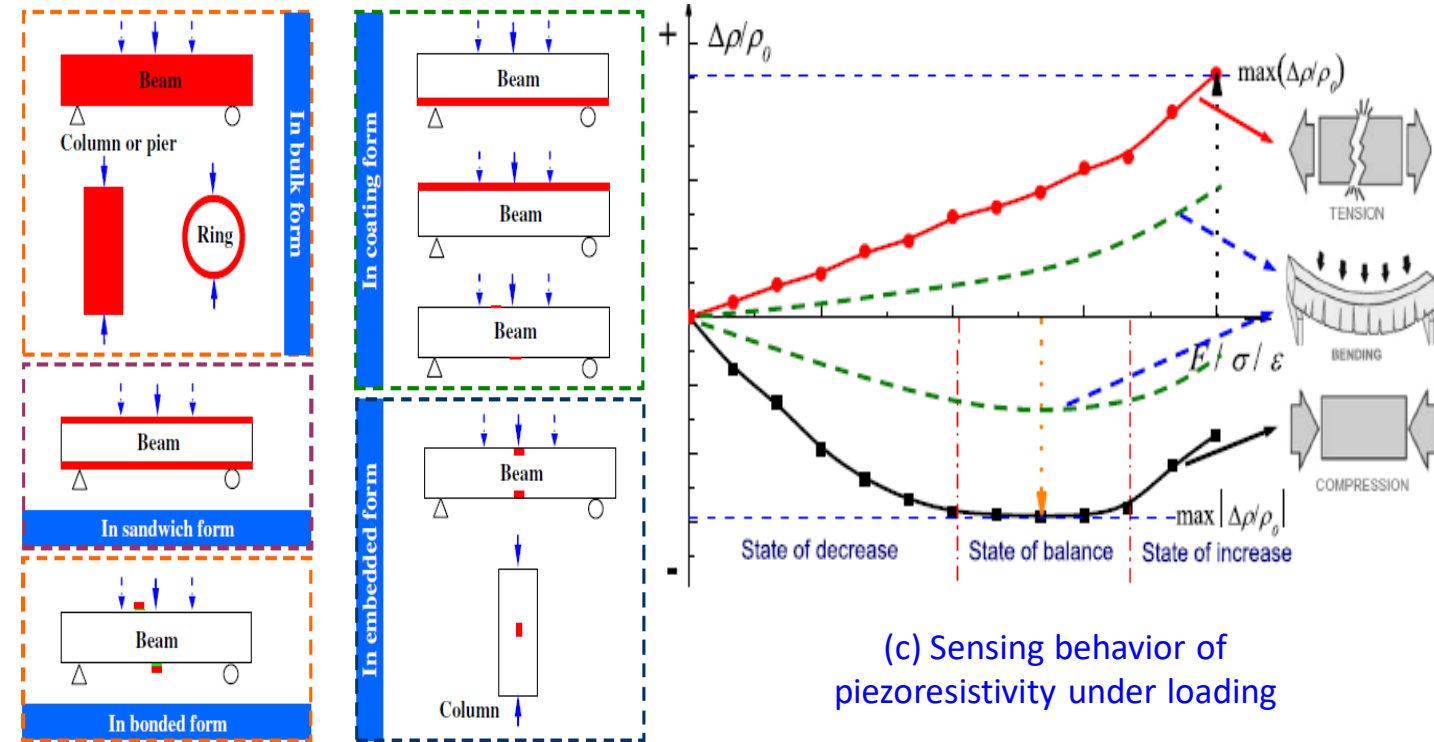
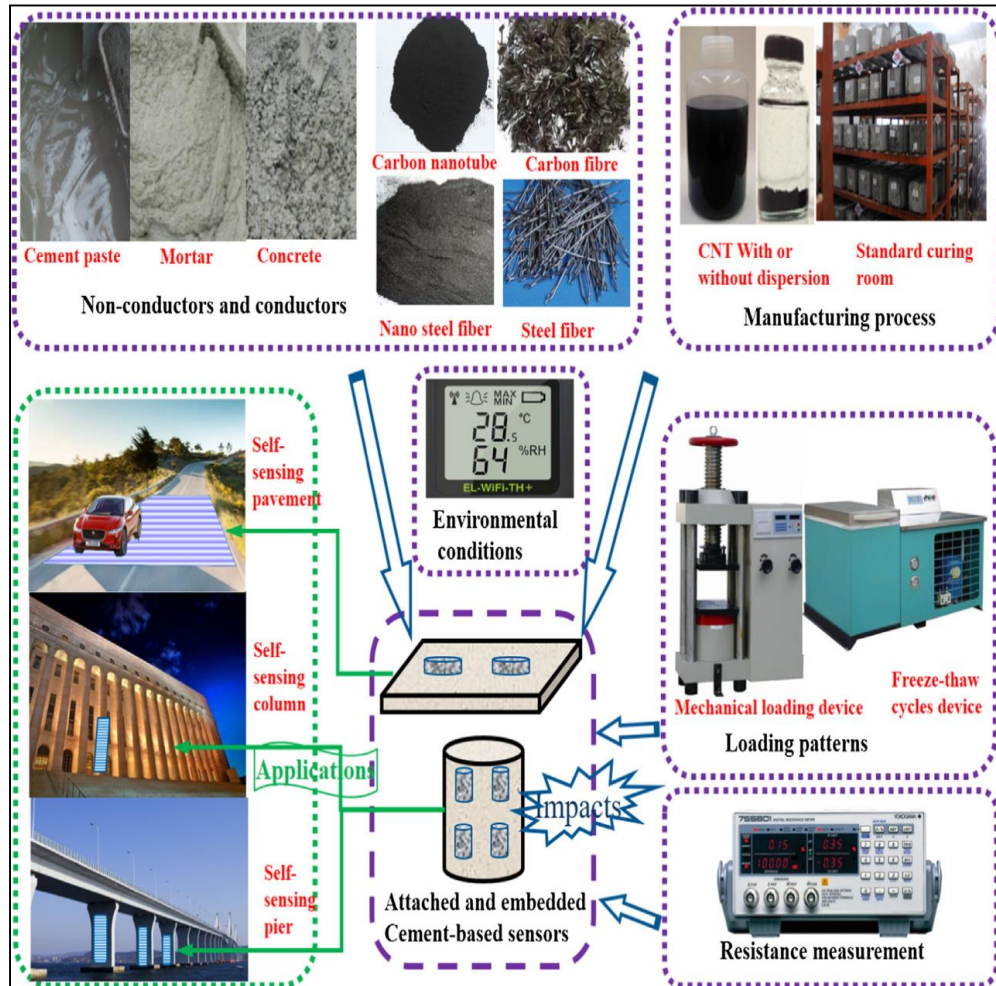


Figure 3 the result of 2-stream CNN accuracy is 98%

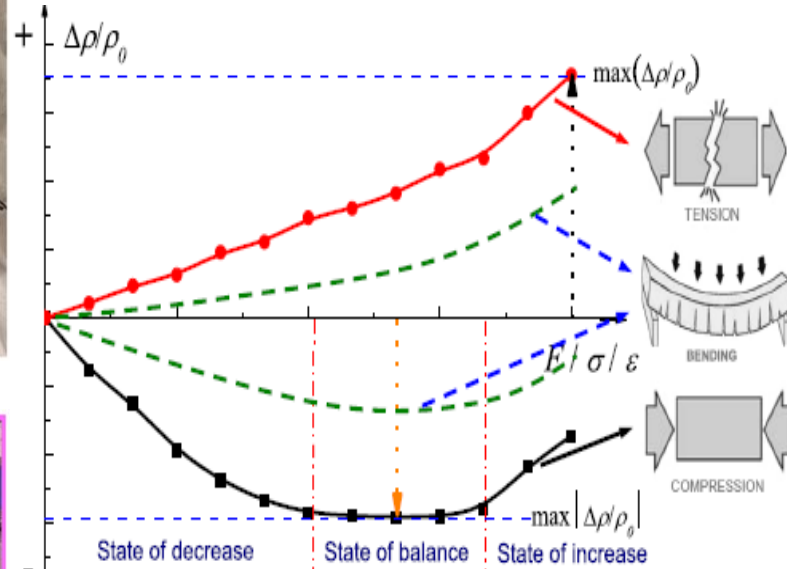
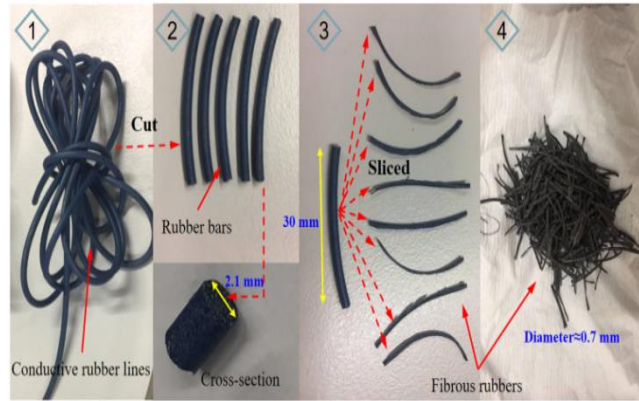
Development and Application of Self-sensing Concrete for Structure Health Monitoring - Dr Wengui LI, ARC future fellow



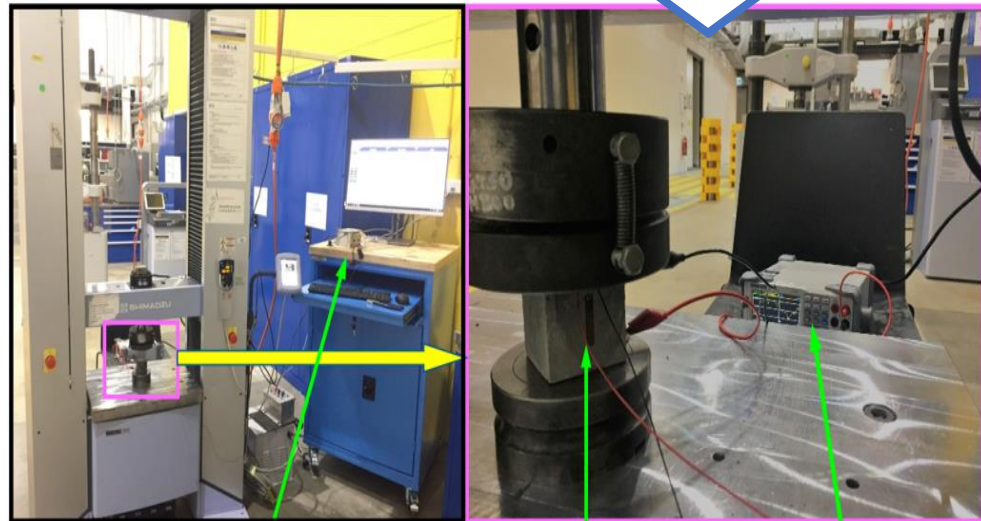
(d) Typical application for structural health monitoring

Development and Application of Self-sensing Concrete for Structure Health Monitoring - Dr Wengui LI, ARC future fellow

(a) Conductive rubber scraps, cut lines and sliced rubber



(c) Sensing behavior of piezoresistivity under loading

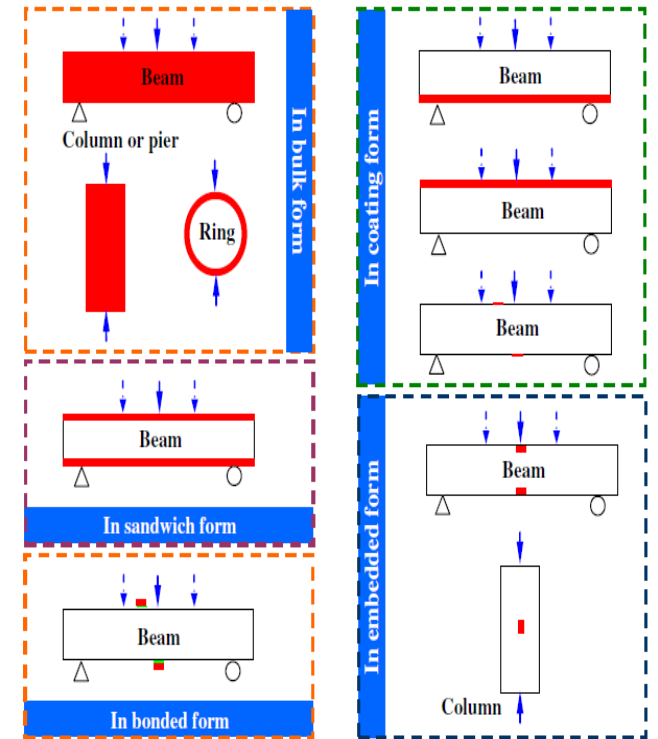


Strain collector

Strain gauge

Multimeter

(b) Compression machine and multimeter for resistance

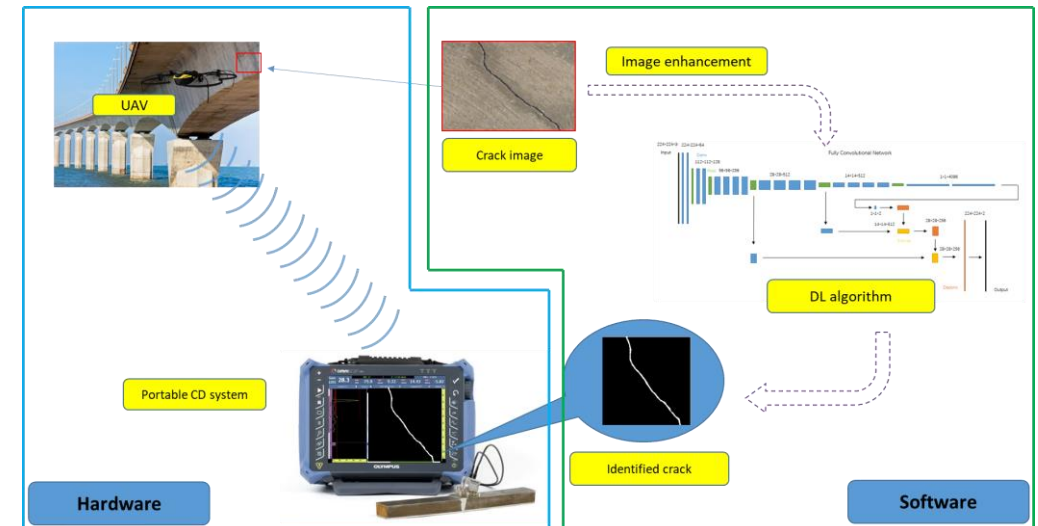


(d) Typical application for structural health monitoring

Bridge UAV crack detection with deep learning

- Dr Yancheng LI, Senior Lecture

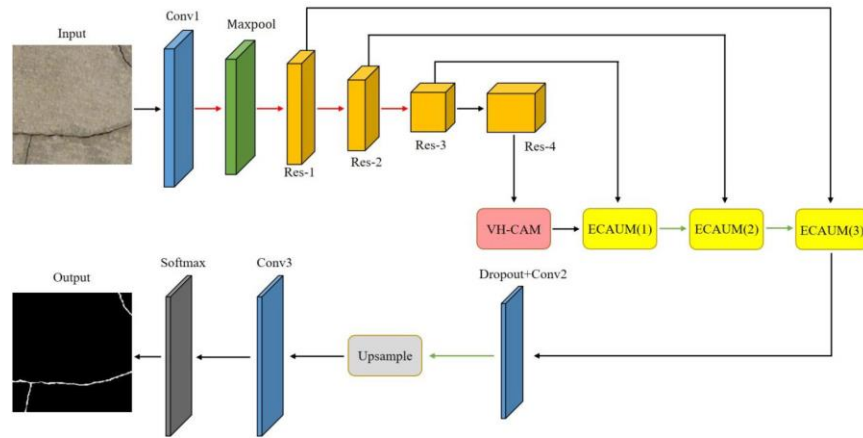
- An integrated system to scan through bridge, to instantly identify cracks and to display identified crack in a portable user interface;
- Key features:
 - Automated crack detection system;
 - Wireless data transmission;
 - Hardware & software interface;
 - Possible crack evaluation and prediction?
- Challenges:
 - Light DL crack detection algorithm with high efficiency and accuracy;
 - Autonomous crack quantification process;
 - Image enhancement, image chopping, and data fusion;
 - Video-based crack detection;



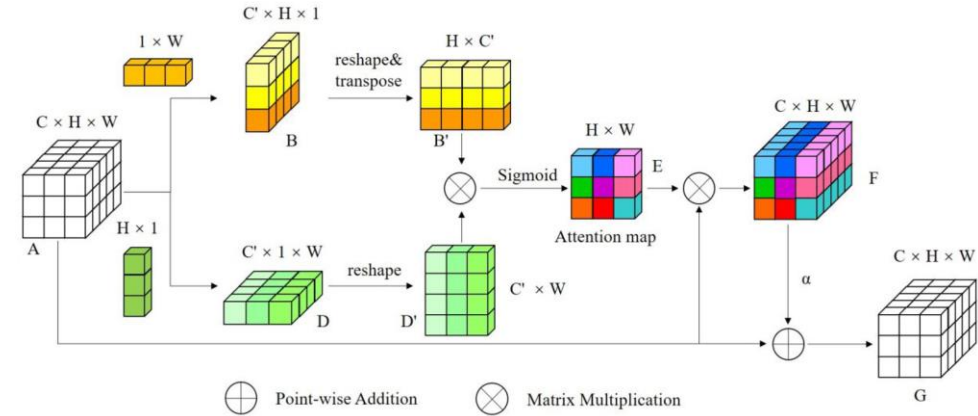
A framework for bridge UAV crack detection

Bridge UAV crack detection with deep learning

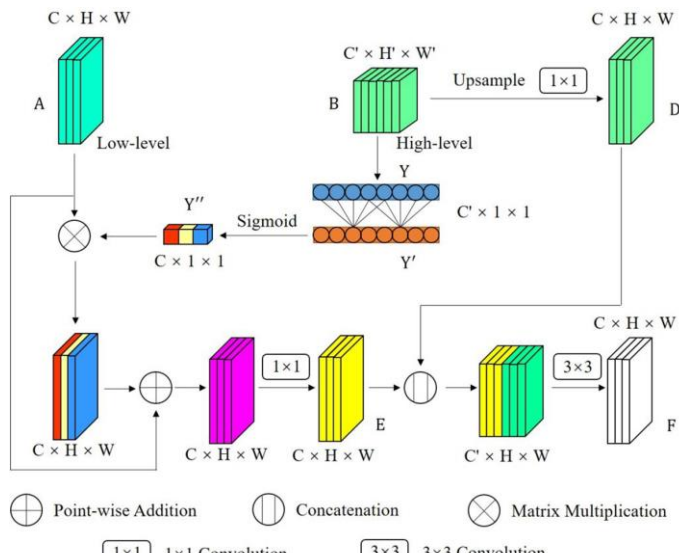
- Dr Yancheng LI, Senior Lecture



Algorithm architecture: ResNet 101 as backbone with two attention mechanisms



Vertical and horizontal compression attention module



Efficient channel attention upsample module

| Models | PA | MPA | MIoU | FWIoU |
|---------------|--------------|--------------|--------------|--------------|
| U-Net | 98.28 | 83.28 | 77.82 | 96.82 |
| Dilated FCN | 98.16 | 80.24 | 75.05 | 96.69 |
| DeepLabv3+ | 98.52 | 83.61 | 77.94 | 97.29 |
| PAN | 98.38 | 81.08 | 75.8 | 96.69 |
| AFFNet | 98.73 | 90.78 | 82.28 | 97.78 |

FCN: fully convolutional network; AFFNet: attention-based feature fusion network; PA: pixel accuracy; MPA: mean pixel accuracy; MIoU: mean intersection over union; FWIoU: frequency weighted intersection over union.

In press with *Structural Health Monitoring*

Work in progress

- **Topic 1:** CrackSegFormer- An Efficient vision transformer-based segmentation network for concrete crack detection (submitted)

Algorithm level: improve the performance of segmentation based vision transformer

- **Topic 2:** A framework for light DL crack segmentation network

Towards hardware development: executable in cost-effective hardware implementation

- **Topic 3:** Automated crack quantification process

Practical based: built on CNN, to identify crack length/width, evaluate crack severity and possible prediction..

- **Topic 4:** Hardware & software interface development

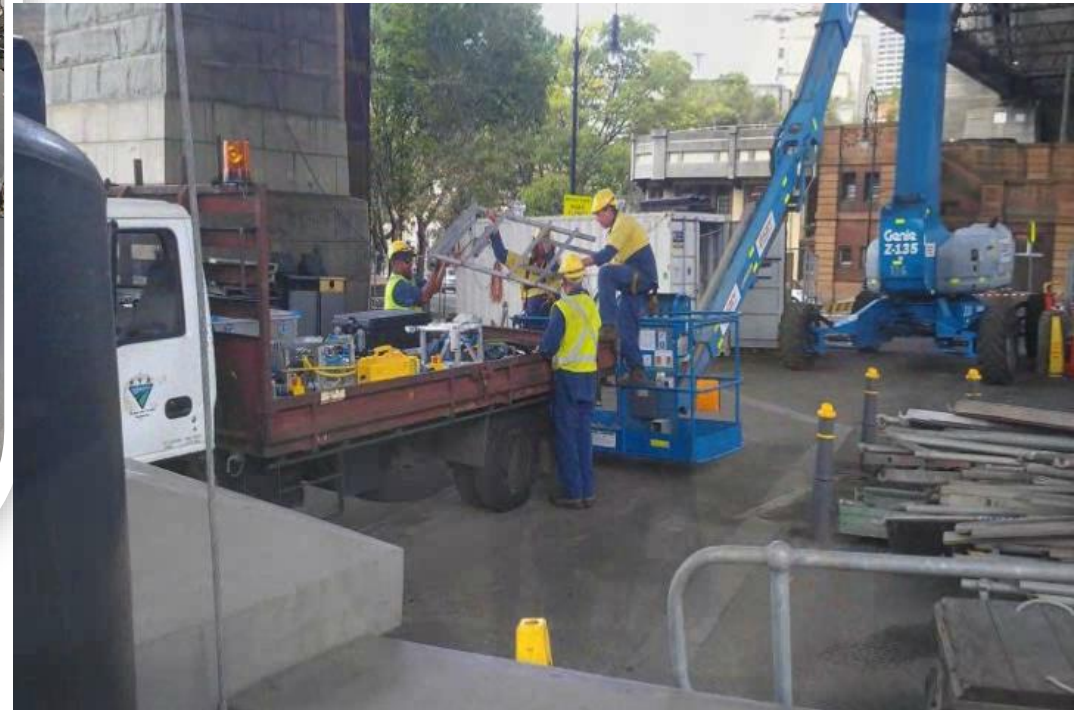
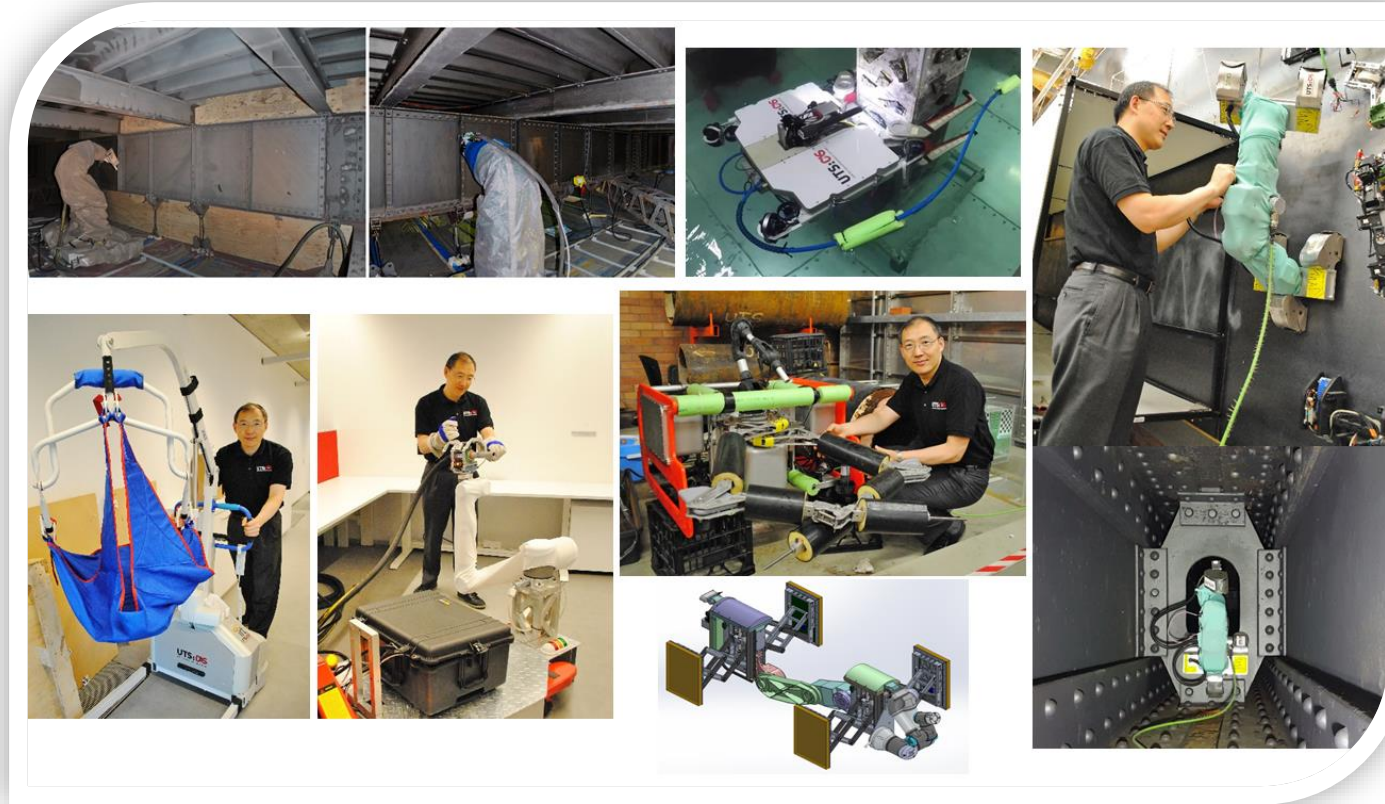
Towards implementation: wireless data transmission, hardware selection, code transplantation (FPGA or MCU), user-friendly interface....

Interest to collaborate? Email: yancheng.li@uts.edu.au;

Intelligent Robotics for steel bridges and structures

- Dist./Prof Dikai Liu, Robotics Institute, UTS

Autonomous robots for steel bridge maintenance (Industry Partners: RTA of NSW, SABRE Autonomous Solutions)



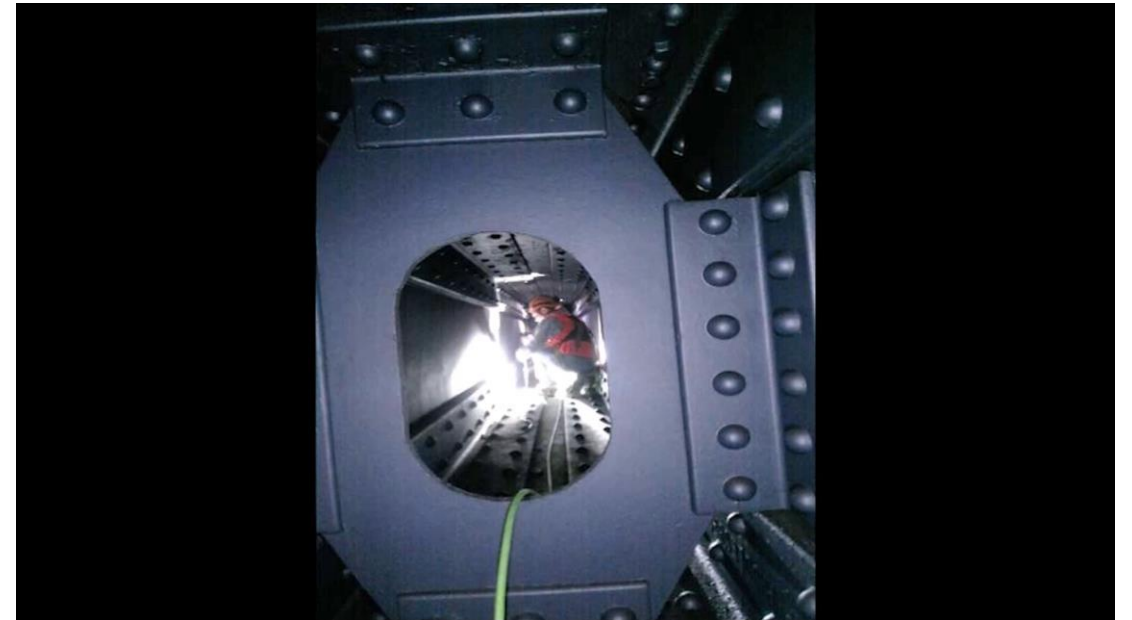
Intelligent Robotics for steel bridges and structures

- Dist./Prof Dikai Liu, Robotics Institute, UTS

Bio-inspired autonomous climbing robots
for inspection of the Sydney Harbour
Bridge (Industry Partners: RMS of NSW)



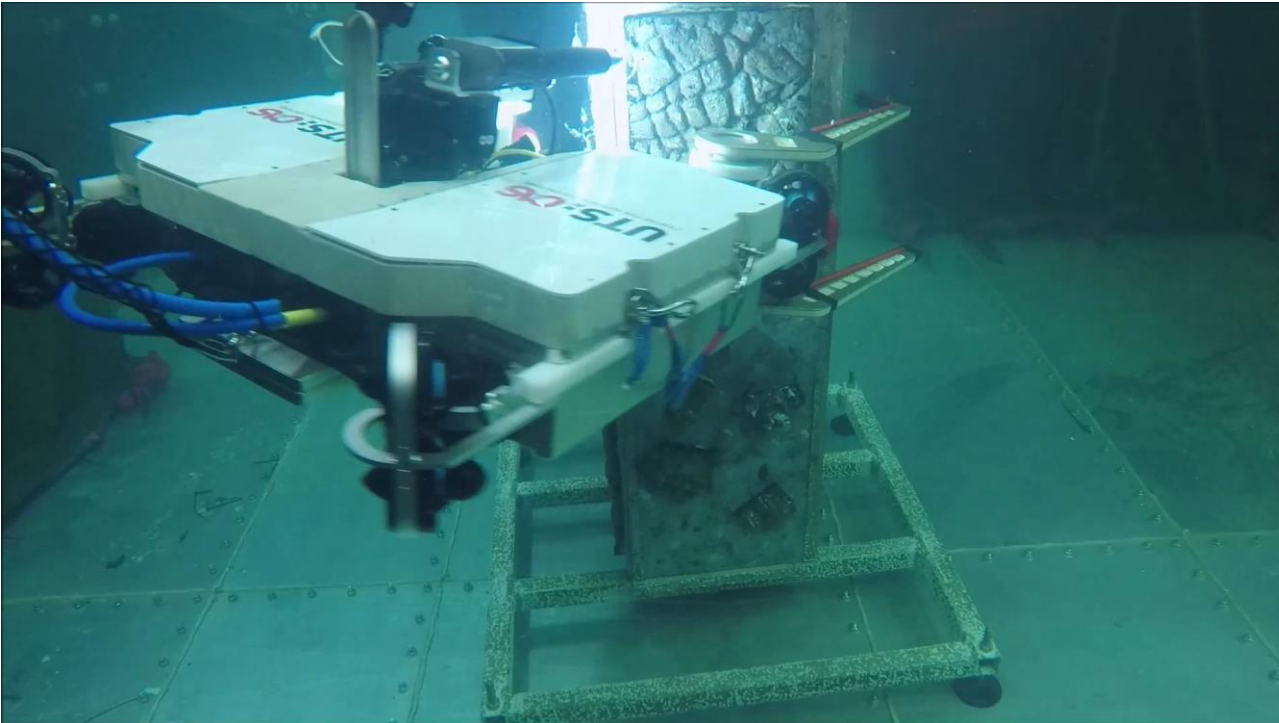
Climbing robots for inspection,
cleaning, and painting in confined
space (Industry partner: TfNSW)



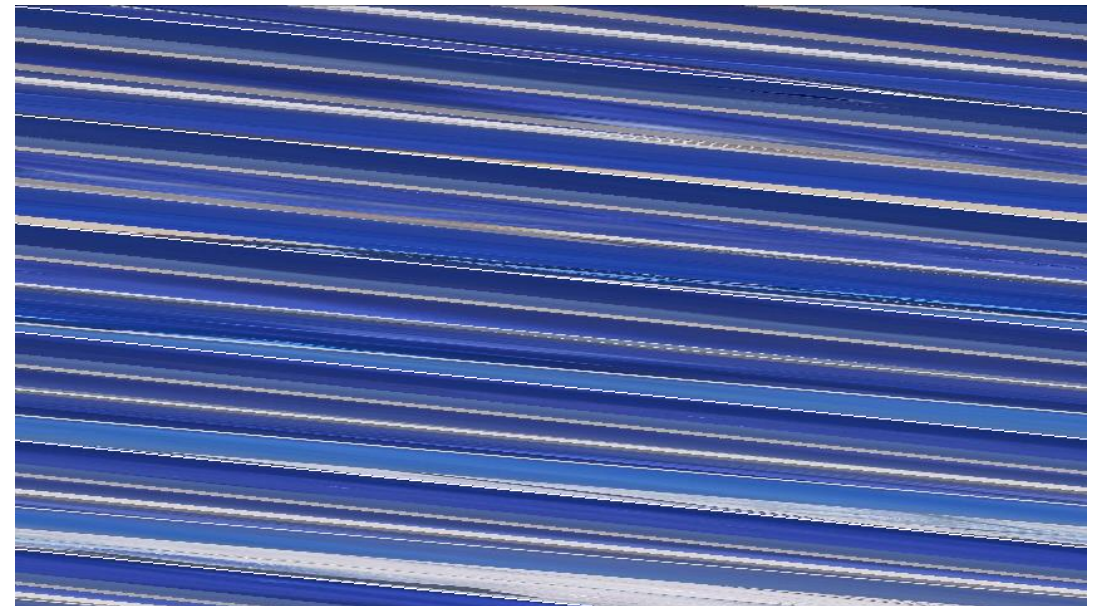
Intelligent Robotics for steel bridges and structures

- Dist./Prof Dikai Liu, Robotics Institute, UTS

Underwater robot for bridge/wharf pile
cleaning and inspection
(Industry Partner: RMS of NSW)



Robots for truss structure inspection,
cleaning and painting
(Industry Partner: TEPCO, Japan)



Summary and Conclusions



The End of the presentation

Thank you for your attention!