

## Drive-by techniques for structural health monitoring of bridges

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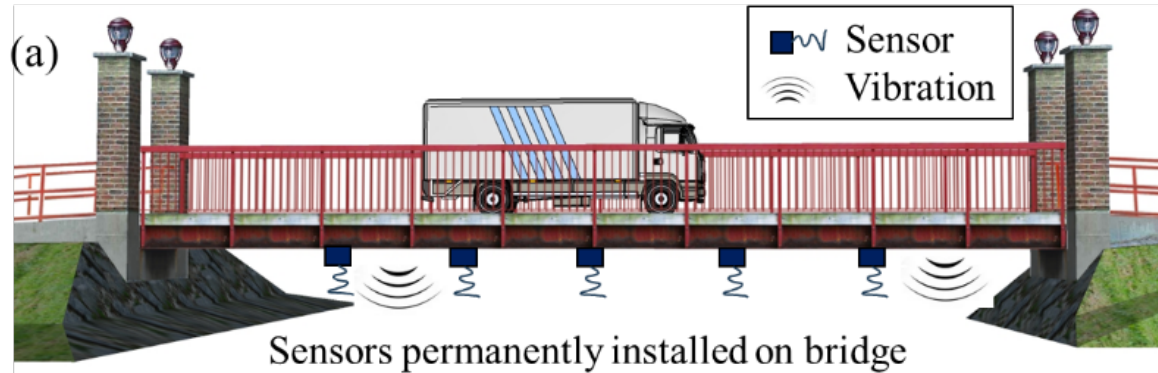
**Curtin University**



# Background and Motivation

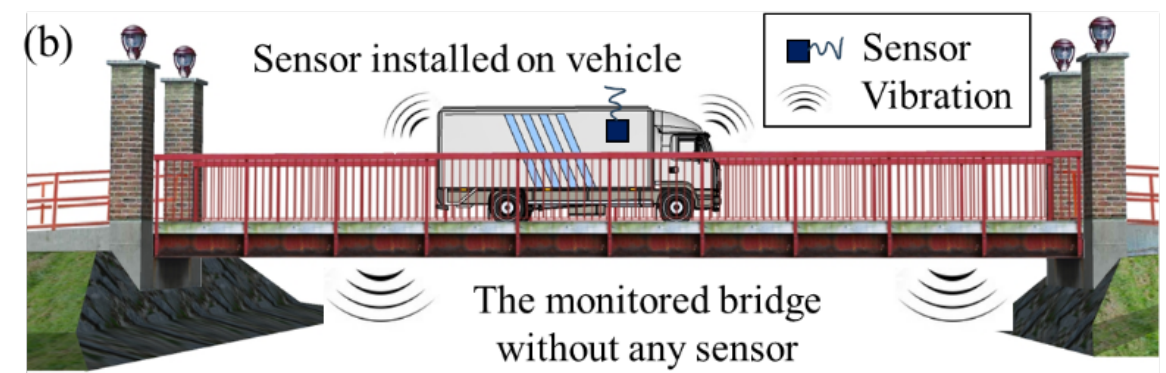
**Problem Statement:** Management of a growing population of aging transportation infrastructure with a limited maintenance budget.

- In Australia, GHD estimated that there is a shortfall of AU\$17.6 billion for maintenance expenditure of infrastructure from 2010 to 2024<sup>1</sup>.
- An estimated 70% of Australia's bridges are more than 50 years old and beyond their design life<sup>2</sup>.



- **One-system-per-bridge basis**, requiring on-site sensor installation.
- **Shorter sensor lifespan** – regular replacement and maintenance.
- **Sparse Spatial Resolution** – sensors installed in limited locations.

Contact-type sensor-based SHM



- **One vehicle, many bridges** – enables city-scale inspections.
- **Easier maintenance** – sensors replaced on vehicles, not bridges.
- **Dense spatial resolution** – vehicle scans the whole bridge span.

In-direct (drive-by) SHM

## Role of drive-by SHM:

Drive-by SHM is not intended to replace fixed monitoring systems, but to provide more frequent condition information for bridges where permanent instrumentation is not feasible and routine inspections are too infrequent.



# Background and Motivation

- Bridge natural frequency identified from crowdsensing drive-by measurement<sup>c</sup>

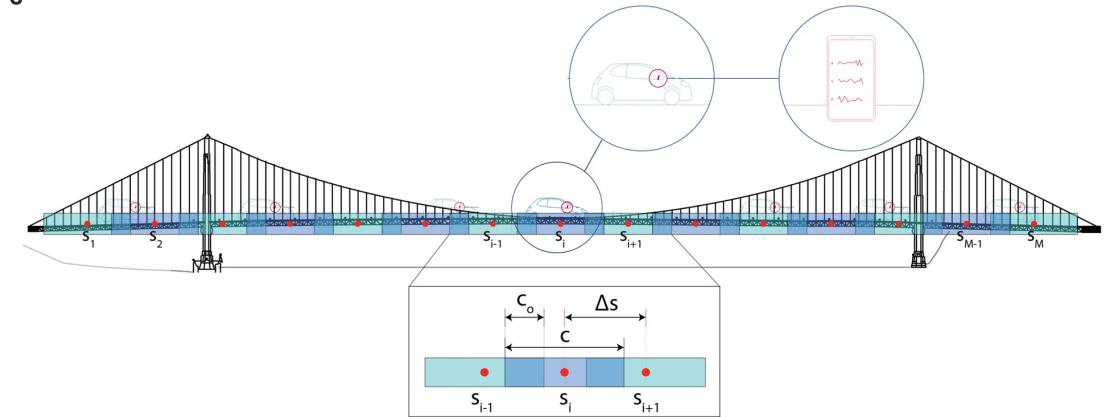
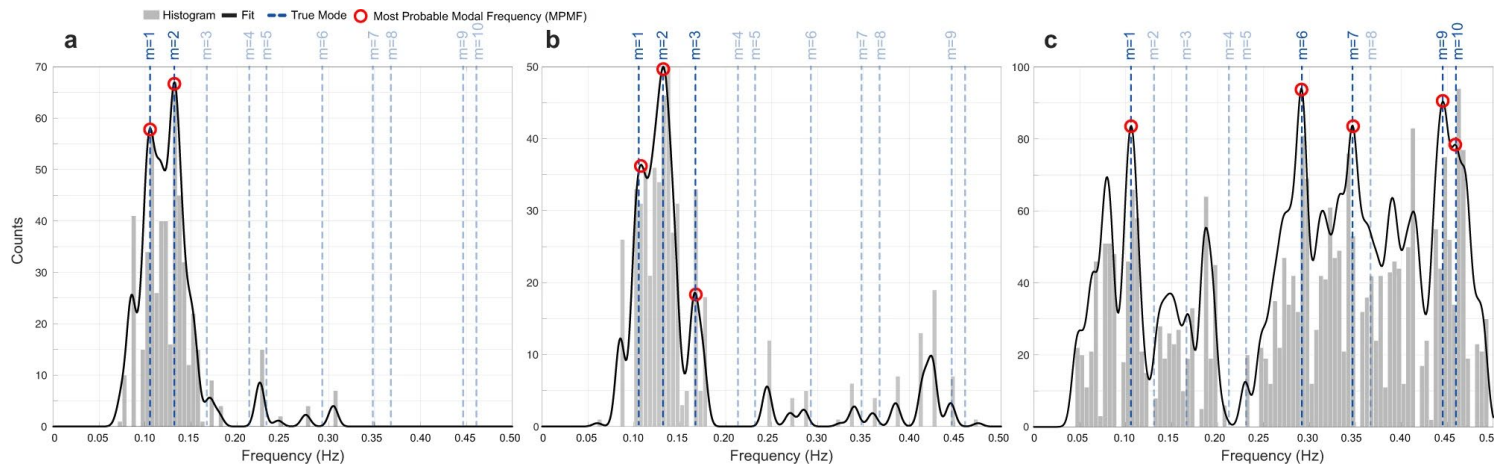


Illustration of controlled data collection on golden gate bridge.



**Final estimates of probability density functions (PDFs) from smartphone vehicle trip (SVT) data.**

- 102 trips of data recorded with two smartphones;
- Multi-order bridge natural frequencies can be identified.

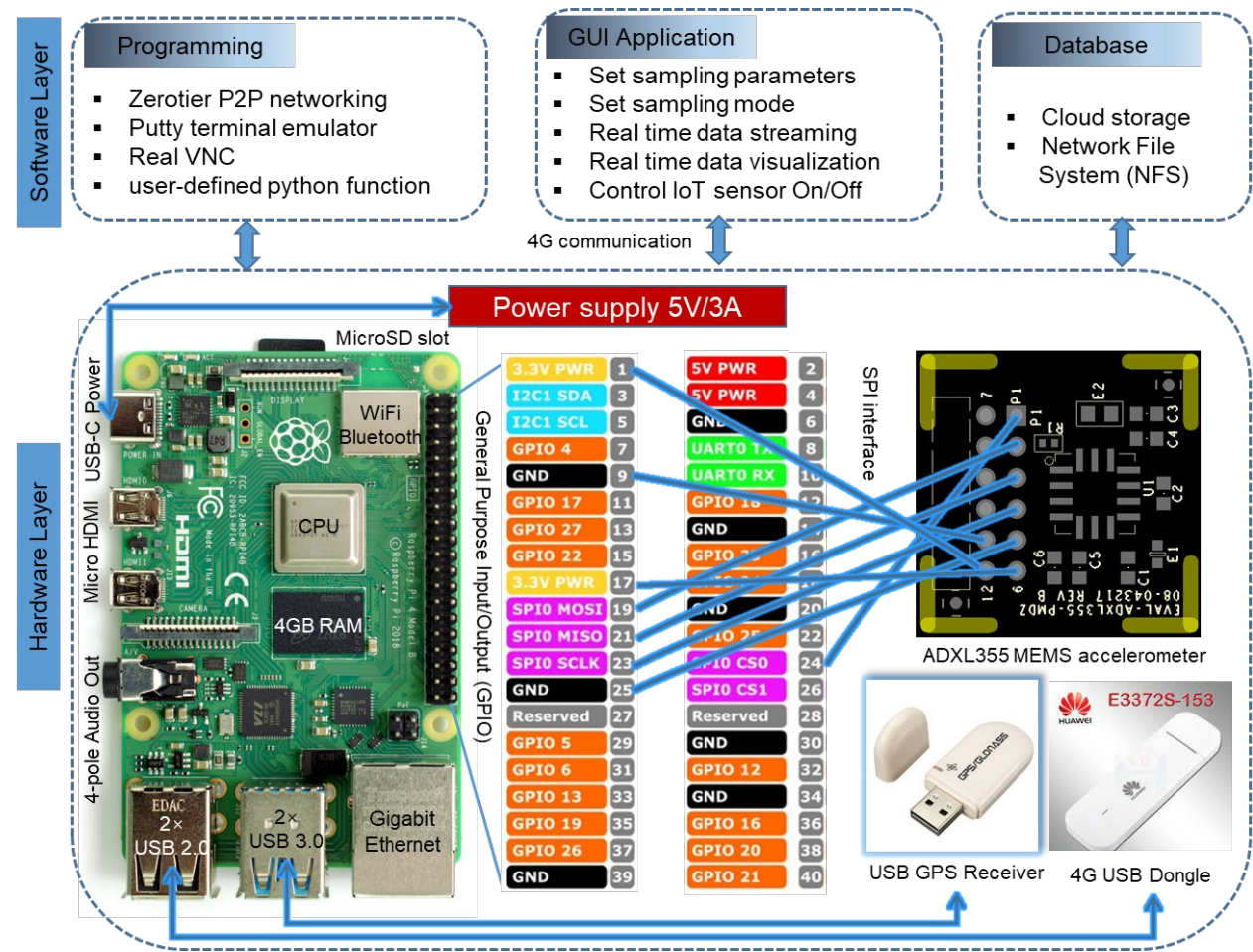
# Framework

- Crowdsensing data collection and pre-processing
- Vehicle-road/bridge contact-point response identification
- Bridge modal parameter identification from drive-by measurement
- Bridge damage sensitive feature extraction from drive-by measurement

# Study 1: Toward city-level mobile crowdsensing data collection

## Internet of Thing (IoT) Sensing System development

### prototype of IoT sensor node



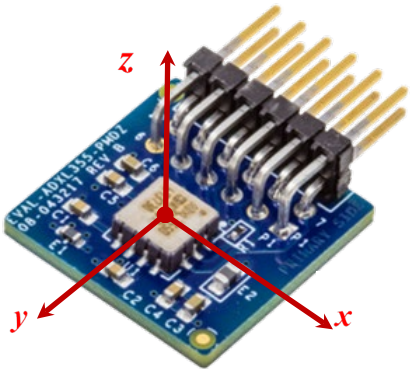
### Functional requirement descriptions of IoT sensing system

| No. | Descriptions                                                                                                                                |
|-----|---------------------------------------------------------------------------------------------------------------------------------------------|
| R1  | Acquisition and transmission of time labelled acceleration responses, temperature and GPS data with desirable accuracy.                     |
| R2  | System time synchronization with the internet.                                                                                              |
| R3  | Real-time signal processing capacity, for example, analyse the acceleration responses in frequency domain and apply programmable filter.    |
| R4  | Sending commands to the sensing unit from remote terminal computer to modify the sensor sampling rate, duration and control the start/stop. |
| R5  | Remote GUI surface enables real-time visualization of collected data.                                                                       |
| R6  | Data storage in sensor node and cloud storage for post-processing of history data.                                                          |

### The component and system architecture of the IoT sensing platform for drive-by based SHM



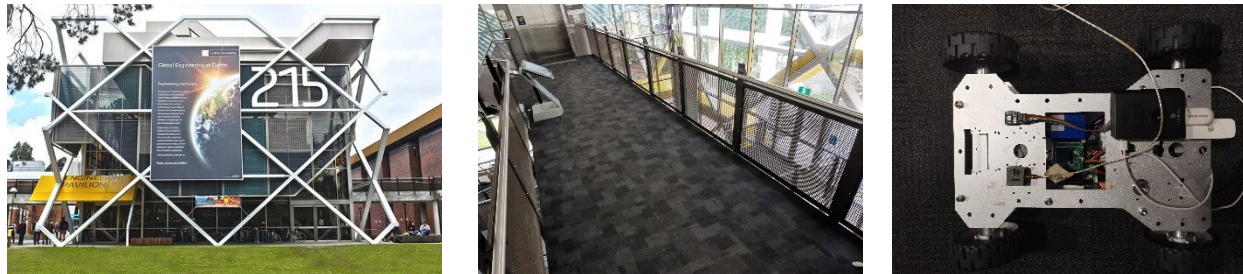
Fully assembled prototype of IoT sensing node



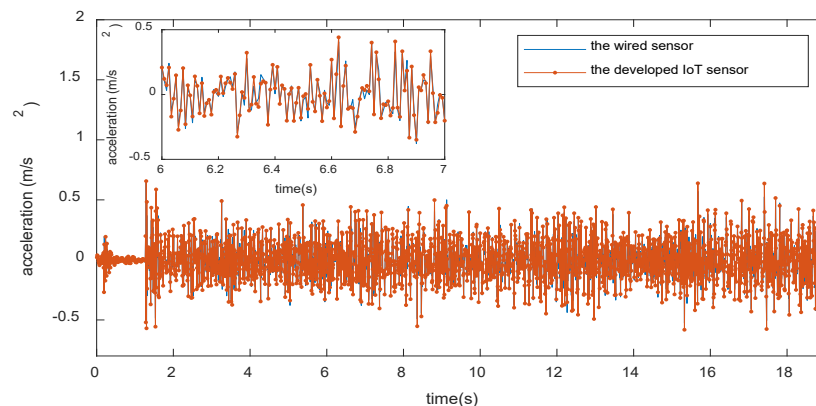
ADXL355 accelerometer

# Study 1: Toward city-level mobile crowdsensing data collection

## Internet of Thing (IoT) Sensing System development

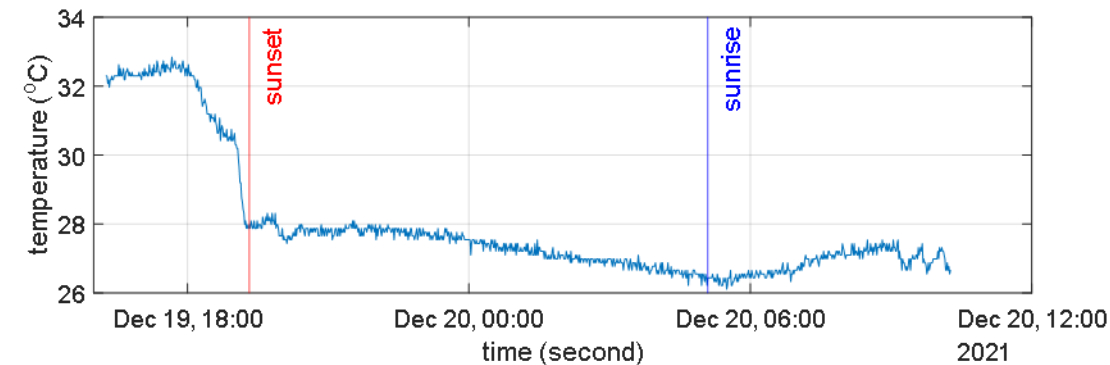


(a) Elevation view of Building 215, (b) drive-by test conducted on the third floor footbridge and (c) the vehicle model and placement of developed IoT sensor and wired accelerometer.

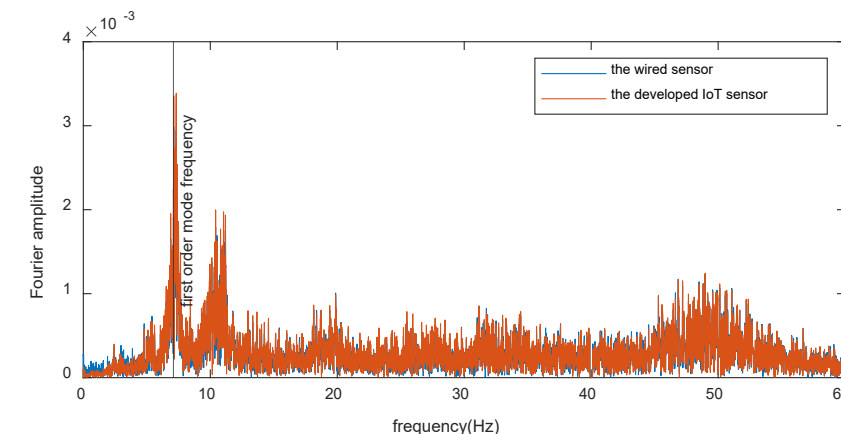


Acceleration time series

## Temperature sensor



Evolution of indoor temperature Building 216, Curtin University. The red and blue vertical line represent the sunset and sunrise time.

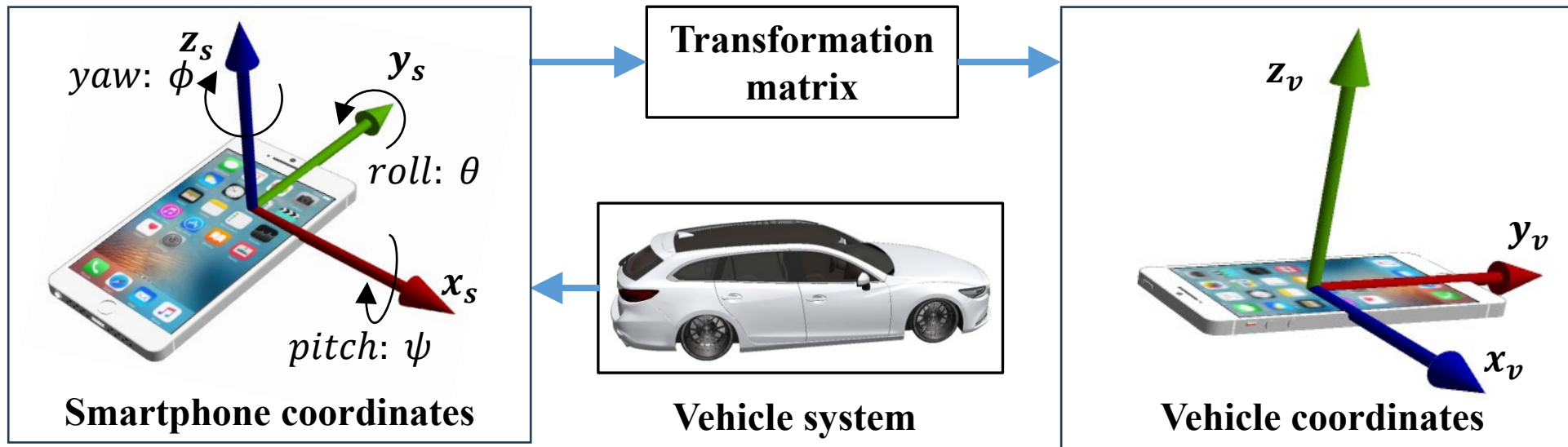


Frequency spectrum

- The correlation coefficient is 0.9753, NRMSE is 1.44%.
- The first order natural frequency (around 7Hz) is correctly identified from the drive-by measurement by using the developed IoT sensing system.

# Study 1: Toward city-level mobile crowdsensing data collection

## ▪ Data-driven sensor coordinate re-orientation to vehicle coordinate



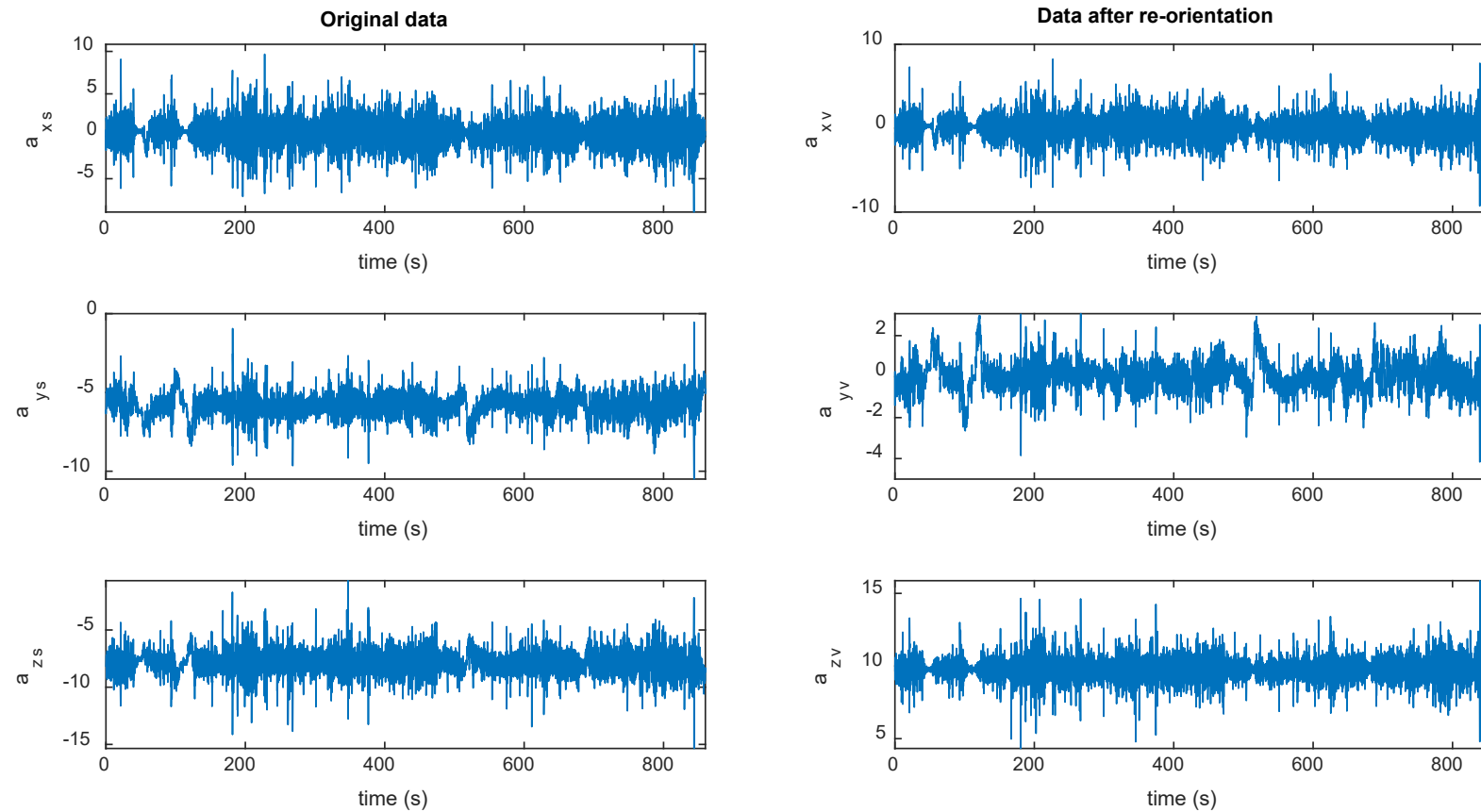
$$\begin{bmatrix} x_v \\ y_v \\ z_v \end{bmatrix} = \overbrace{\begin{bmatrix} \cos(\phi) & -\sin(\phi) & 0 \\ \sin(\phi) & \cos(\phi) & 0 \\ 0 & 0 & 1 \end{bmatrix}}^{\text{yaw}} \overbrace{\begin{bmatrix} \cos(\psi) & 0 & \sin(\psi) \\ 0 & 1 & 0 \\ -\sin(\psi) & 0 & \cos(\psi) \end{bmatrix}}^{\text{pitch}} \overbrace{\begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\theta) & -\sin(\theta) \\ 0 & \sin(\theta) & \cos(\theta) \end{bmatrix}}^{\text{roll}} \begin{bmatrix} x_s \\ y_s \\ z_s \end{bmatrix}$$

### Physical information incorporated for pitch, roll and yaw angle estimation:

1. Overall acceleration is strictly equal to 1g when the smartphone is stationary or in uniform linear motion.
2. A force field aligned with the direction of the vehicle's motion is generated when the vehicle accelerates or decelerates in a straight line

# Study 1: Toward city-level mobile crowdsensing data collection

- Data-driven sensor coordinate re-orientation to vehicle coordinate



1. The acceleration responses of  $a_{xv}$  and  $a_{yv}$  equal to zero, while  $a_{zv}$  closes to 1g, which confirms that the sensor coordinate is aligned with the vertical direction after re-orientation.

# Study 2: Vehicle-road contact-point response identification

## Field road test



(a)

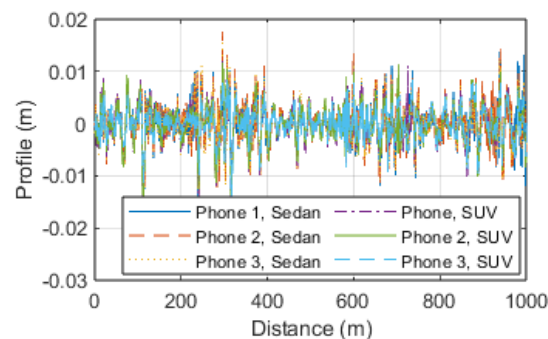


(b)

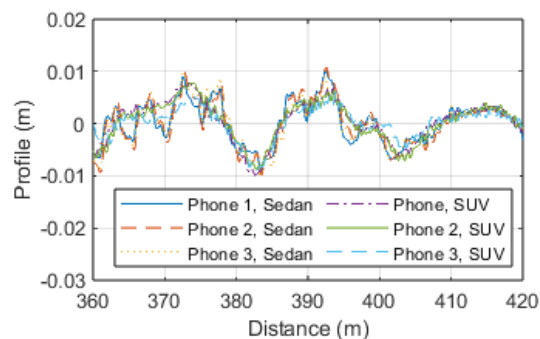


(c)

Data collection instruments. (a) Mazda 6, (b) MG ZS Excite and (c) In-cabin smartphones.

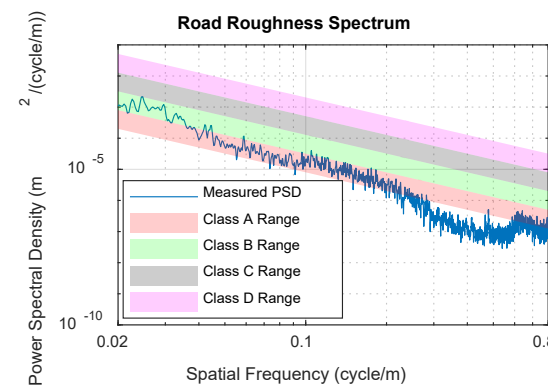


(a)

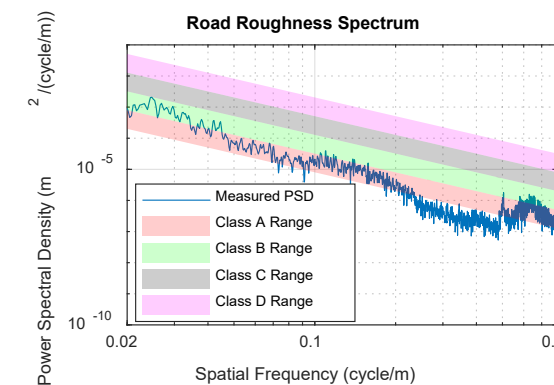


(b)

Road roughness estimation using three different phone setups and two vehicle types: (a) 1000 m distance and (b) 60 m distance (zoomed-in view).



(a)

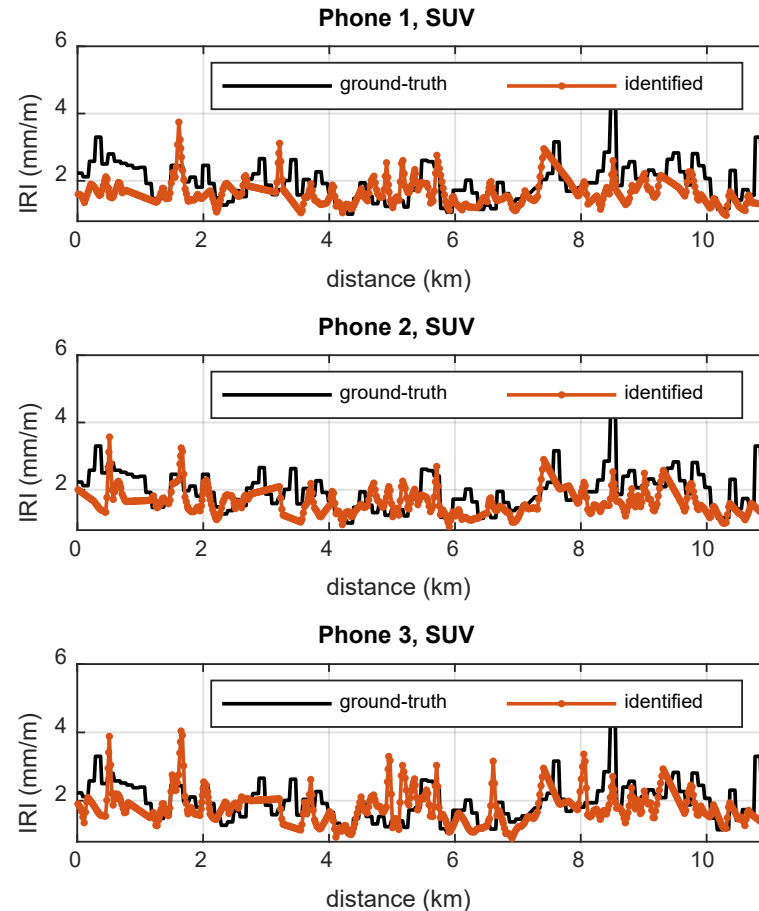
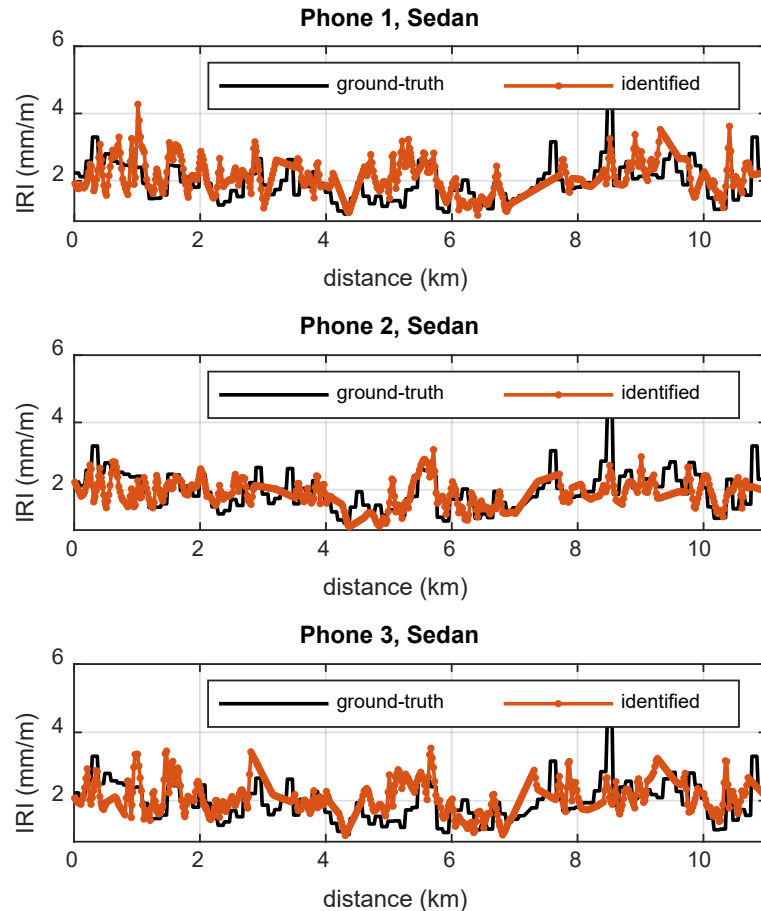


(b)

Power spectral densities of road roughness identified from the proposed approach using data measured from: (a) Phone 1, Sedan and (b) Phone 1, SUV.

# Study 2: Vehicle-road contact-point response identification

## Field road test



1. Overall, it could be observed that the IRI estimated from each combination of phone and vehicle configuration agree with the IRI ground-truth, with relative errors between 22%~29%.
2. Temporal discrepancies exist between the ground-truth IRI data, collected via laser road profile survey vehicles in December 2022, and the field tests conducted for this study in October 2024.

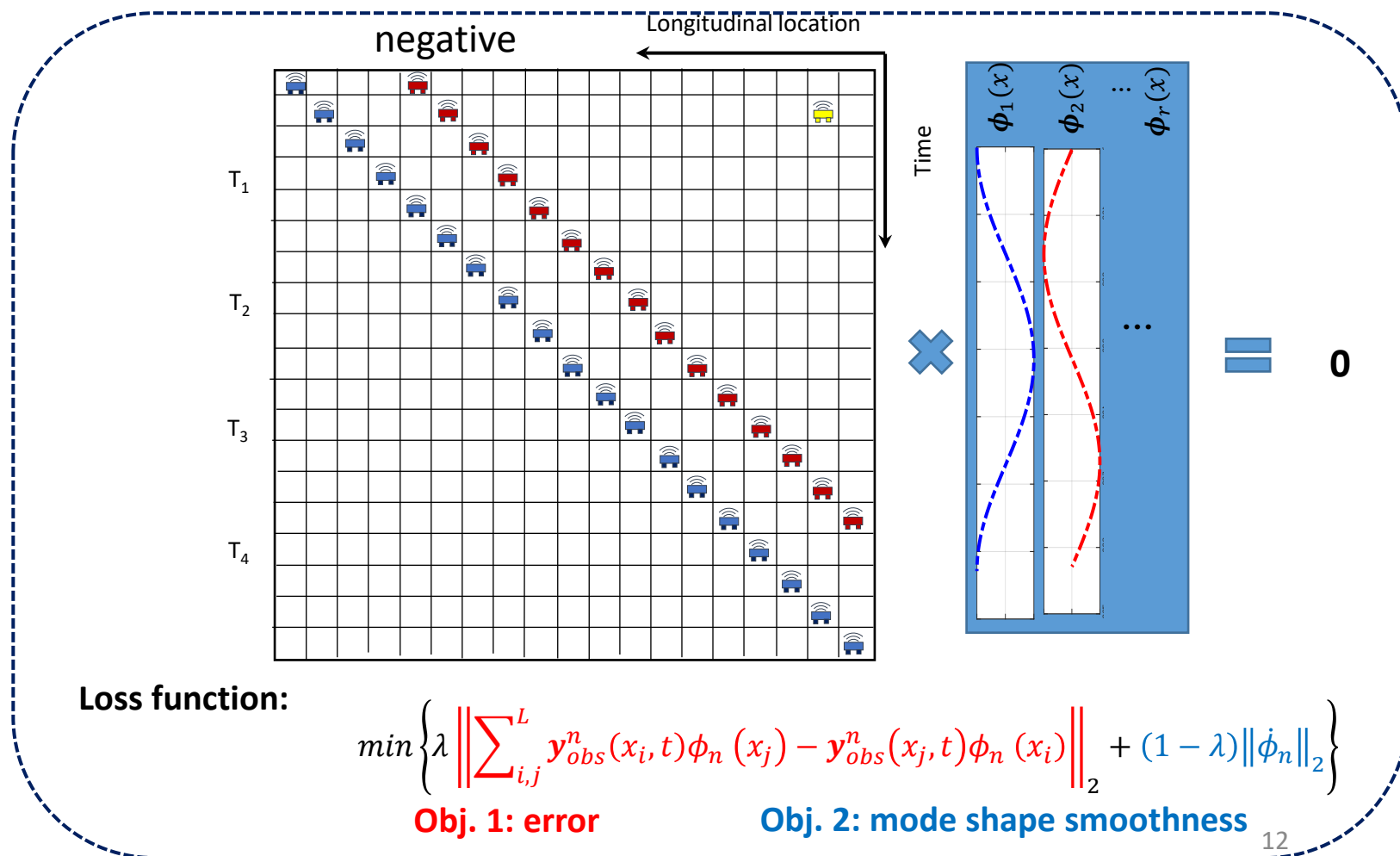
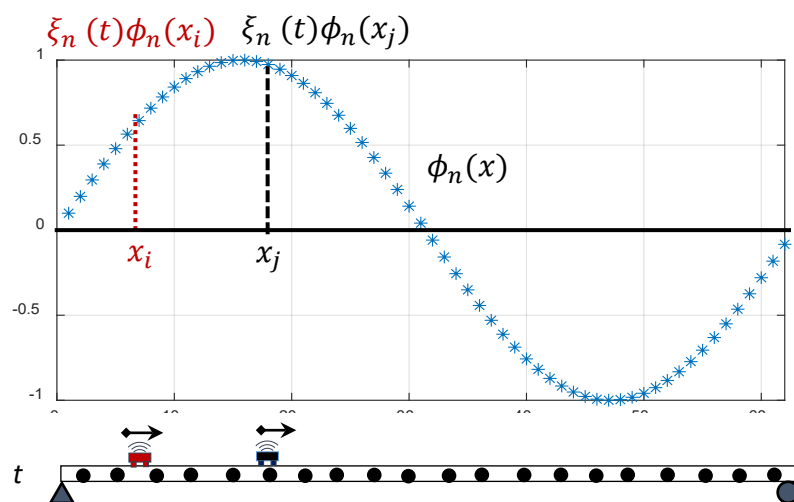
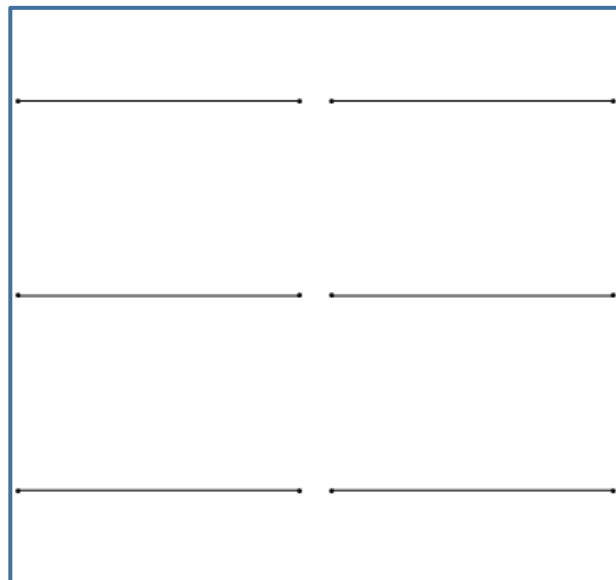
**Comparison of IRI ground-truth and the IRI values estimated from the proposed approach with different phones and vehicle configurations.**

# Study 3: Bridge mode shape identification

- Mobile crowdsensing framework for drive-by-based dense spatial-resolution bridge mode shape identification

Response ratio of any two point is a time invariant function of spatial location

$$\frac{y_{obs}^n(x_i, t)}{y_{obs}^n(x_j, t)} = \frac{\xi_n(t) \phi_n(x_i)}{\xi_n(t) \phi_n(x_j)} = \frac{\phi_n(x_i)}{\phi_n(x_j)} \quad \longrightarrow \quad y_{obs}^n(x_i, t) \phi_n(x_j) - y_{obs}^n(x_j, t) \phi_n(x_i) = 0$$

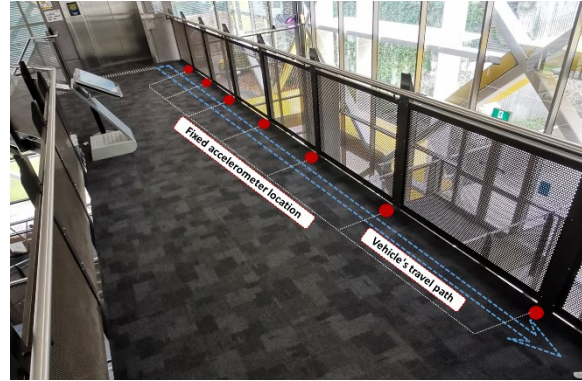


# Study 3: Bridge mode shape identification

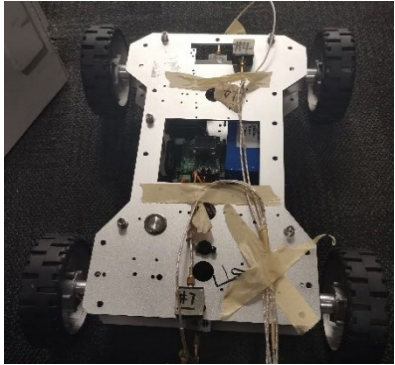
## Case study on a footbridge in Curtin University.



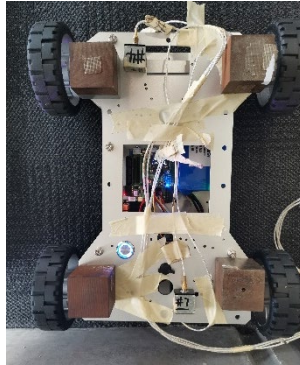
(a)



(b)



(c)



(d)



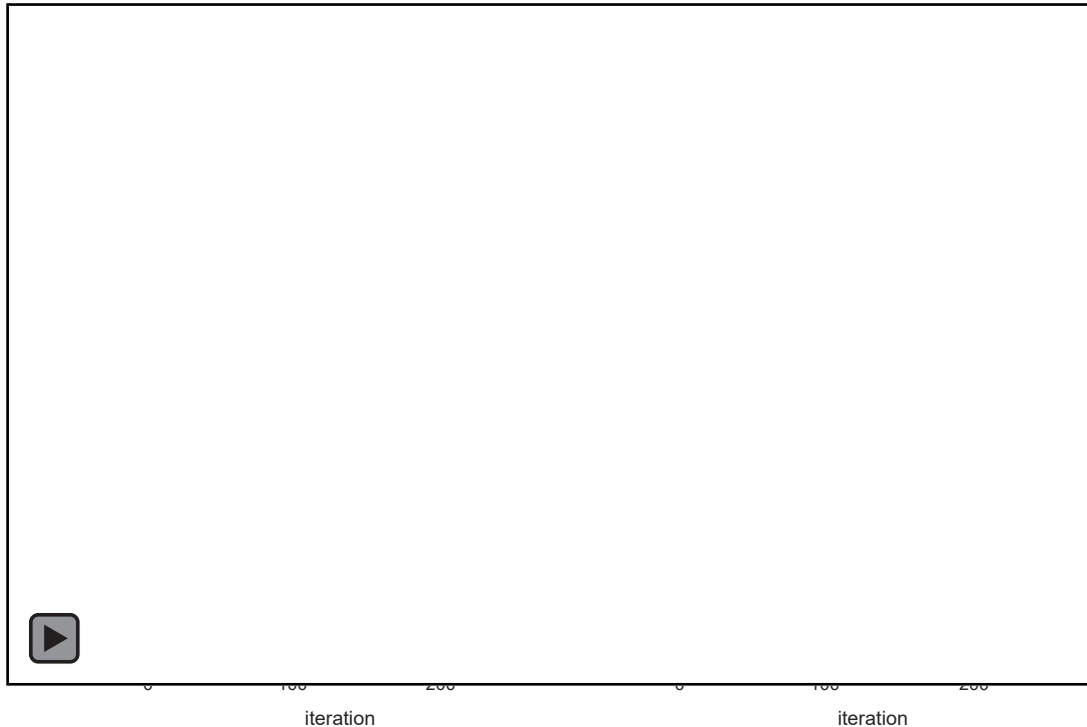
(e)

Elevation view of Building 215 (b) fixed sensor placement and vehicle's travel path on third floor footbridge, (c) in-house made vehicle model for this study, (d) vehicle model with four added mass blocks, and (e) vehicle remote control unit.

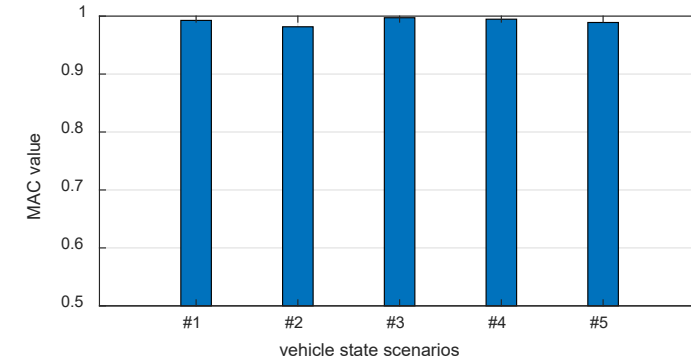
- **Parameters initial for bridge modal test with fixed sensor:**
    - 7 accelerometers evenly distributed along the longitudinal direction;
    - Sampling rate: 500 Hz.
    - Structural responses subjected to ambient and human jump load are recorded.
  - **Parameters initial for drive-by test:**
    - Two vehicle speed: 0.15m/s and 0.3 m/s;
    - Two vehicle mass: add four mass block on vehicle;
    - 13 repeat trips for each scenario;
    - Sampling rate: 500 Hz.
    - Owing to the vehicle mass (about 6kg) is negligible when compared with the mass of full-scale bridge, additional pedestrian load is applied during the test to excite the bridge.
- 2 (mass) × 2 (speeds) × 13 (repeats) = 52 (trips) data are collected.

# Study 3: Bridge mode shape identification

- Case study on a footbridge in Curtin University.



First mode shape identification result and evolution of objectives 1 and 2 over iterations. There was no added mass and the vehicle speed was  $v_2$ . The MAC between the exact and identified mode shape is 0.9972.

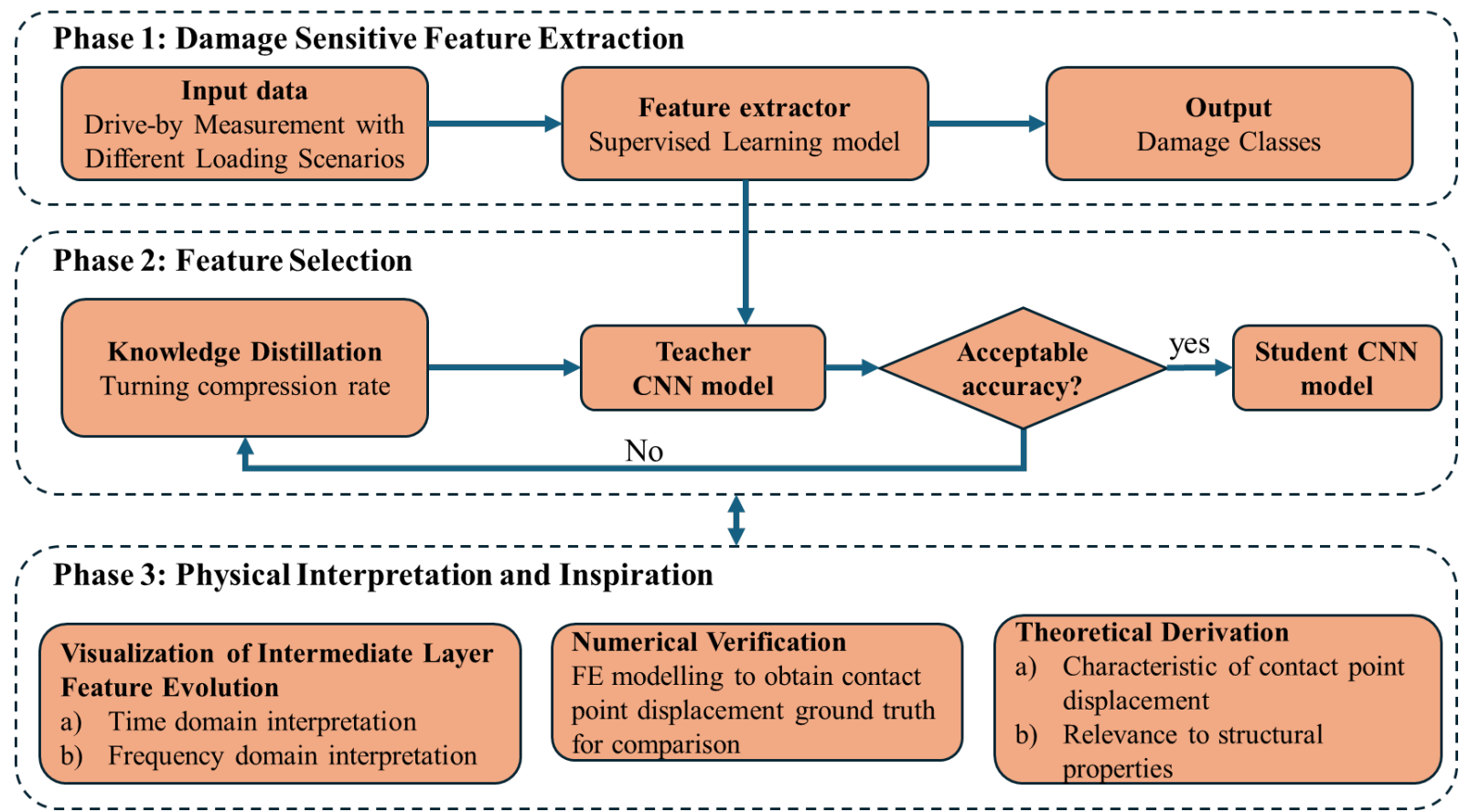


MAC value of five vehicle state scenarios.

- the mode shape identified from the proposed method using crowdsensing measurement agrees well with that from the fixed sensor network.
- The MAC value between the mode shapes identified from the moving sensor and fixed sensor is 0.9972, implying that the proposed method can be a potential alternative for accurately identifying the bridge structure mode shape.

# Study 4: Damage sensitive feature extraction

## Interpretable Damage Sensitive Feature Extraction for Drive-by Structural Health Monitoring Using Knowledge Distillation-based Deep Learning



In phase 1, the drive-by measurements encompassing various structural conditions, vehicle speeds, and weights serve as inputs to the teacher CNN model (feature extractor).

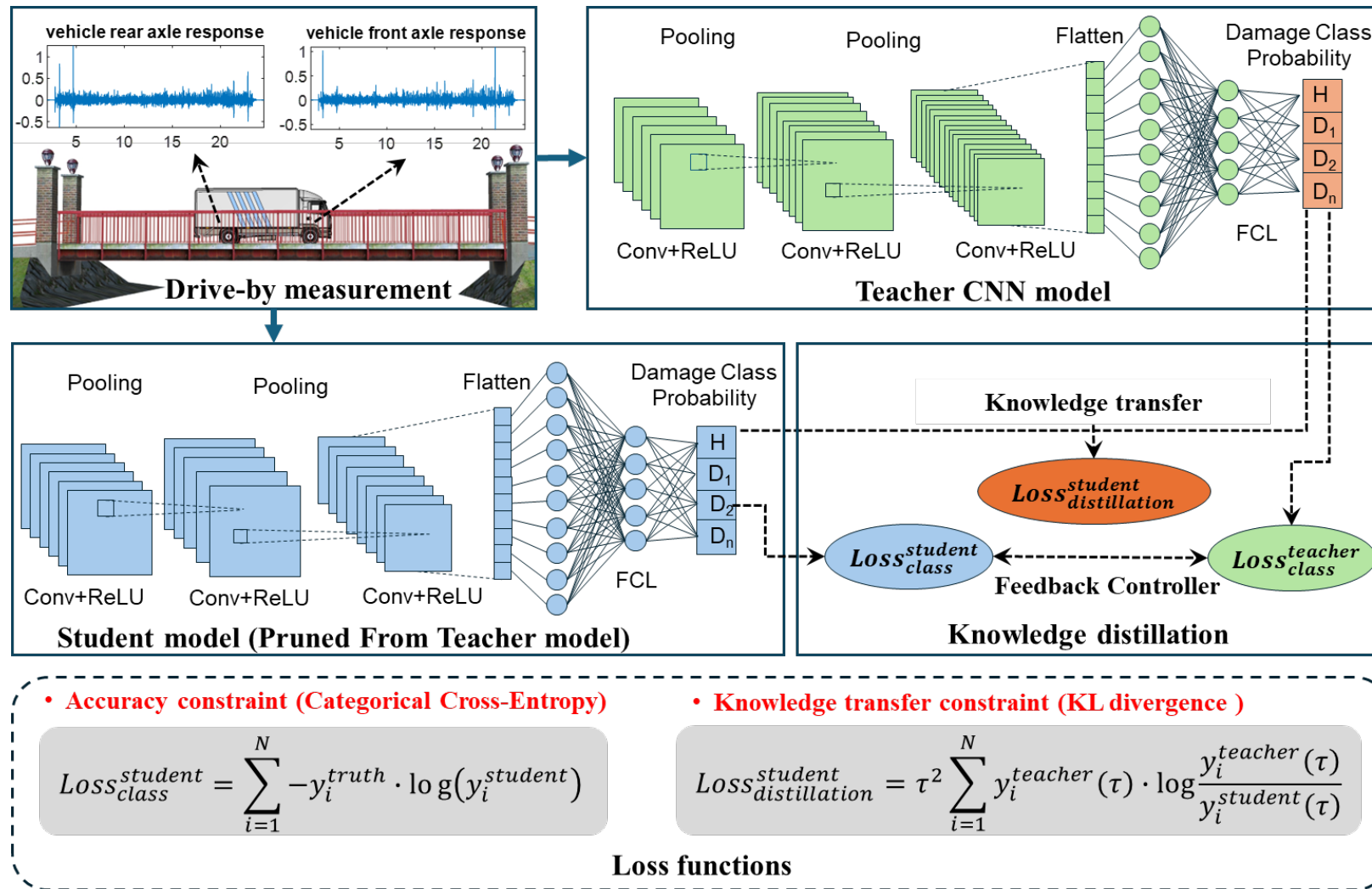
In phase 2, knowledge distillation is introduced in phase 2 to compress the teacher CNN model and thus select a subset of the most representative features.

In phase 3, physical interpretation and inspiration will be provided to understand the features extracted from phases 1-2.

The Flowchart of the research methodology.

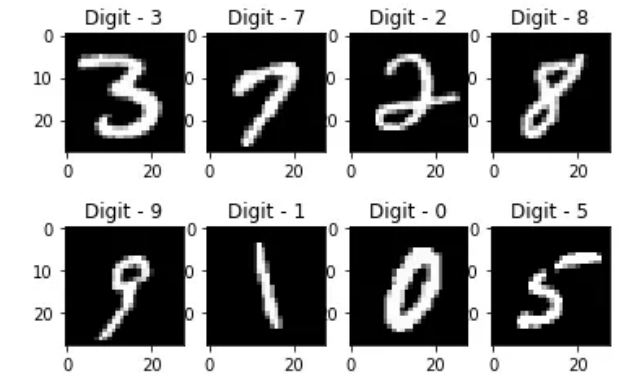
# Study 4: Damage sensitive feature extraction

## Network architecture



Proposed network architecture for extracting damage-sensitive features from drive-by measurements.

## How knowledge transfer works



Input: 7, output logit values:

$$z_{digit=7}^{teacher} = 0.9, z_{digit=2}^{teacher} = 0.09, z_{digit=1}^{teacher} = 0.01.$$

The softened probability vector:

$$y_i^{teacher}(\tau) = \frac{\exp(z_i^{teacher}/\tau)}{\sum_{j=1}^N \exp(z_j^{teacher}/\tau)}$$

When  $\tau = 1$ :  $y_{digit=7}^{teacher}(1) = 0.5389$ ,

$y_{digit=2}^{teacher}(1) = 0.2397$ ,  $y_{digit=1}^{teacher}(1) = 0.2213$ .

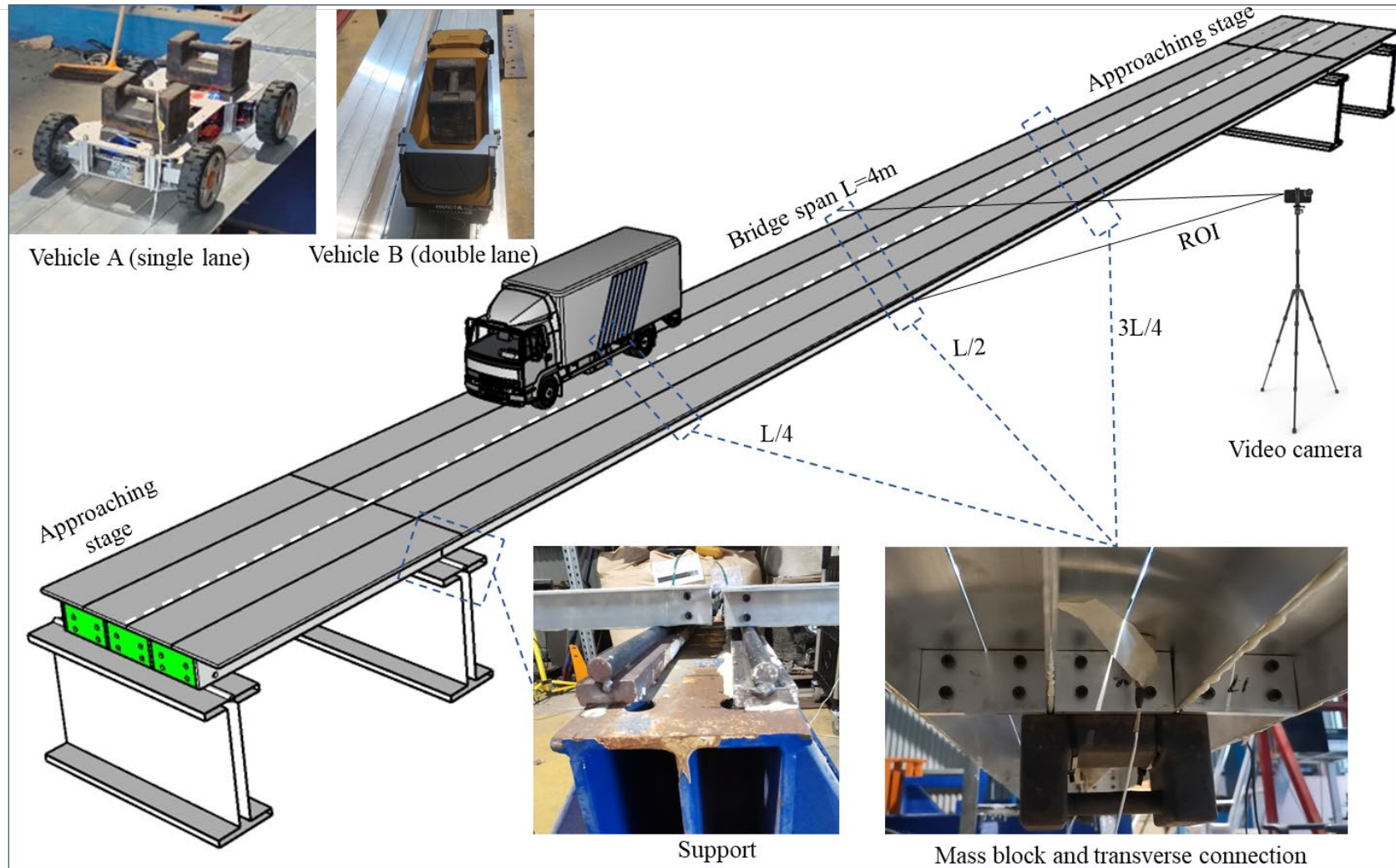
When  $\tau = 5$ :  $y_{digit=7}^{teacher}(5) = 0.3721$ ,

$y_{digit=2}^{teacher}(5) = 0.3165$ ,  $y_{digit=1}^{teacher}(5) = 0.3114$ .

When  $\tau > 1$ , The knowledge transfer constraint will force the student model to mimic the teacher model by paying more attention to the false predictions.

# Study 4: Damage sensitive feature extraction

## Experiment setup



Schematic of the instrument layout

## Bridge and vehicle model:

- Four Tee section girder
- First two order modal frequencies are 5.7Hz and 22Hz.
- Two vehicles: one lane and two lane car model

## Test variables:

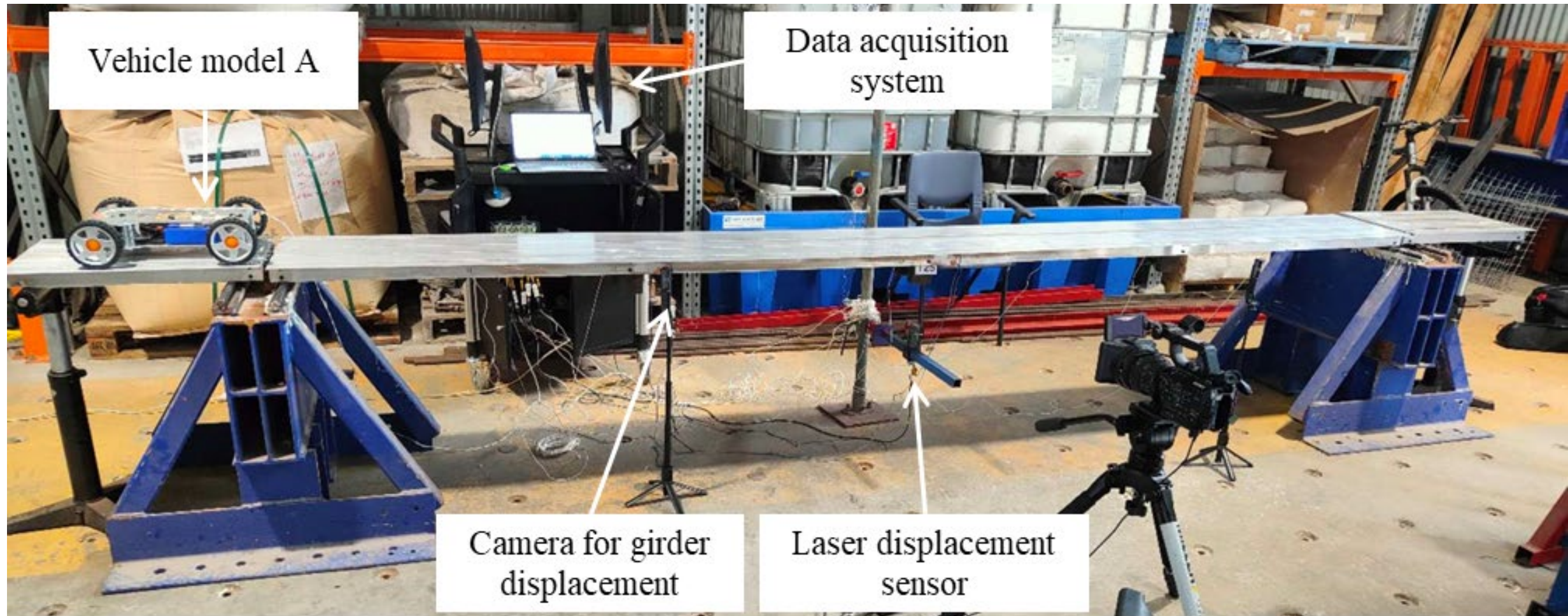
- Structural damage: health state, remove of C6, remove of C3 & C6
- Vehicle speed: static, slow, medium and fast mode
- Vehicle weight: unloaded car, add 5kg, 10kg mass block, respectively.
- Each combination of above three variable record 20 trips data.

## Sensors & equipment:

- Accelerometer, 6 on the bridge longitudinal direction, 2 on vehicle
- One laser displacement sensor on the mid-span
- Four strain gauges on  $1/4$  and  $1/2$  span, respectively.
- Two cameras on  $1/4$  and  $1/2$  span, respectively

# Study 4: Damage sensitive feature extraction

- Experiment setup



# Study 4: Damage sensitive feature extraction

## Feature selection using knowledge distillation

Network structure along with the output shape of each layer

| Type                | Output size   |                 |                 |                 |
|---------------------|---------------|-----------------|-----------------|-----------------|
|                     | Teacher model | Student model 1 | Student model 2 | Student model 3 |
| Layer (type)        | Output Shape  | Output Shape    | Output Shape    | Output Shape    |
| covn_0 (Conv2D)     | 2×2048×8      | 2×2048×6        | 2×2048×4        | 2×2048×2        |
| LeakyReLU           | 2×2048×8      | 2×2048×6        | 2×2048×4        | 2×2048×2        |
| conv_1 (Conv2D)     | 2×2048×16     | 2×2048×12       | 2×2048×8        | 2×2048×4        |
| batch_normalization | 2×2048×16     | 2×2048×12       | 2×2048×8        | 2×2048×4        |
| LeakyReLU           | 2×2048×16     | 2×2048×12       | 2×2048×8        | 2×2048×4        |
| AveragePooling2D    | 2×1024×16     | 2×1024×12       | 2×1024×8        | 2×1024×4        |
| conv_2 (Conv2D)     | 2×1024×32     | 2×1024×24       | 2×1024×16       | 2×1024×8        |
| batch_normalization | 2×1024×32     | 2×1024×24       | 2×1024×16       | 2×1024×8        |
| LeakyReLU           | 2×1024×32     | 2×1024×24       | 2×1024×16       | 2×1024×8        |
| AveragePooling2D    | 1×512×32      | 1×512×24        | 1×512×16        | 1×512×8         |
| conv_3 (Conv2D)     | 1×512×8       | 1×512×6         | 1×512×4         | 1×512×2         |
| batch_normalization | 1×512×8       | 1×512×6         | 1×512×4         | 1×512×2         |
| LeakyReLU           | 1×512×8       | 1×512×6         | 1×512×4         | 1×512×2         |
| AveragePooling2D    | 1×128×8       | 1×128×6         | 1×128×4         | 1×128×2         |
| flatten (Flatten)   | 1×1024        | 1×1024          | 1×1024          | 1×1024          |
| dense_0 (Dense)     | 1×128         | 1×128           | 1×128           | 1×128           |
| dense_1 (Dense)     | 1×32          | 1×32            | 1×32            | 1×32            |
| output_layer        | 1×4           | 1×4             | 1×4             | 1×4             |

Compress rate:      0%                  25%                  50%                  75%

Accuracy:            98.26%            96.01%            94.07%            85.28%

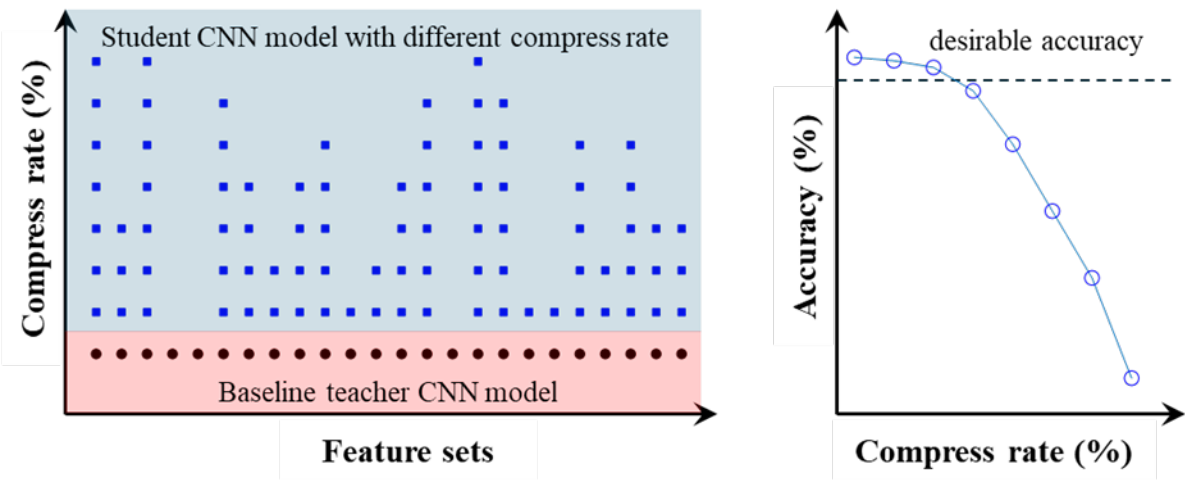
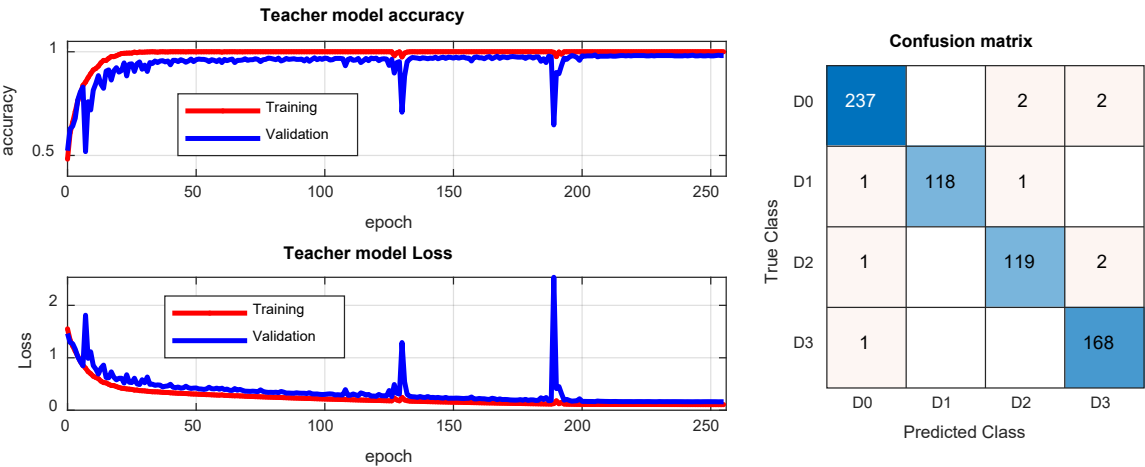


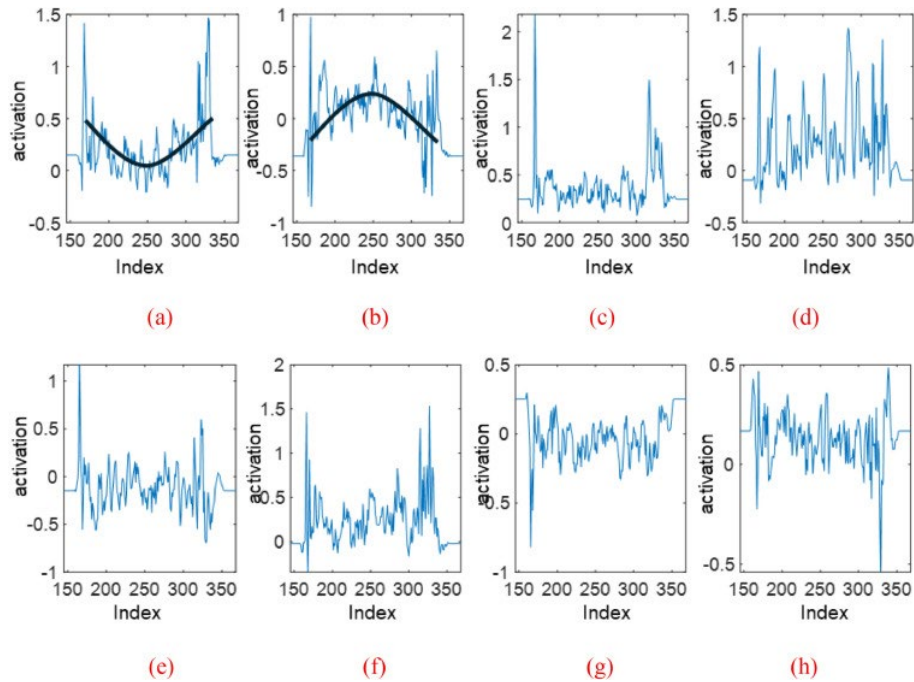
Illustration of feature selection using knowledge distillation.



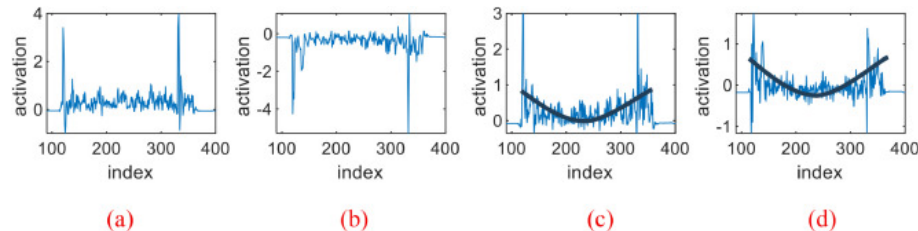
(a) the evolution of teacher CNN model accuracy and loss and (b) confusion matrix.

# Study 4: Damage sensitive feature extraction

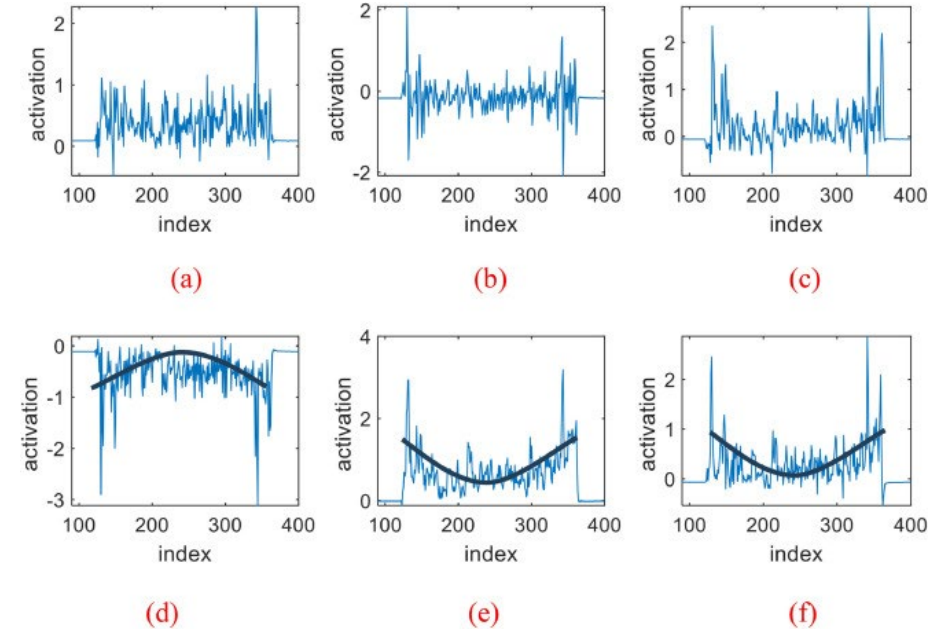
- final convolutional layer of the teacher CNN model



- final convolutional layer of the student CNN model with a compression rate of 50 %



- final convolutional layer of the student CNN model with a compression rate of 25 %



- The number of features decrease with the compression rate;
- The features resembling the vehicle-bridge contact point displacement are always preserved, indicating that these features are more important than the others removed during the model compression.

# Summary

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- **Mobile crowdsensing drive-by data collection is low-cost and scalable, and of potential for city-level bridge SHM.**
- **Vehicle-road contact-point response can be identified from drive-by measurement by incorporating physics-informed constraints.**
- **Dense spatial-resolution bridge mode shape identification can be identified from drive-by measurements by incorporating mobile crowdsensing.**
- **Preliminary study demonstrate deep learning technique is of potential to extract damage sensitive feature from drive-by measurements.**

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**Peng, Z., Li, J., & Hao, H. (2023). Development and experimental verification of an IoT sensing system for drive-by bridge health monitoring. Engineering Structures, 293, 116705.**

**Peng, Z., Li, J., Hao, H., Fan, G., & Karunaratne, L. (2026). Smartphone-based vehicle-road contact-point response identification with unknown vehicle parameters. Engineering Structures, 347, 121701.**

**Peng, Z., Li, J., Hao, H., & Yang, N. (2023). Mobile crowdsensing framework for drive-by-based dense spatial-resolution bridge mode shape identification. Engineering Structures, 292, 116515.**

**Peng, Z., Li, J., Zhong, Y., & Hao, H. (2025). Interpretable Damage Sensitive Feature Extraction for Drive-by Structural Health Monitoring Using Knowledge Distillation-based Deep Learning. Journal of Sound and Vibration, 119303.**

# Thank you for your attention and comments!

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