From Experiments to In-Service: Encoding Structural Damage via Speaker Recognition

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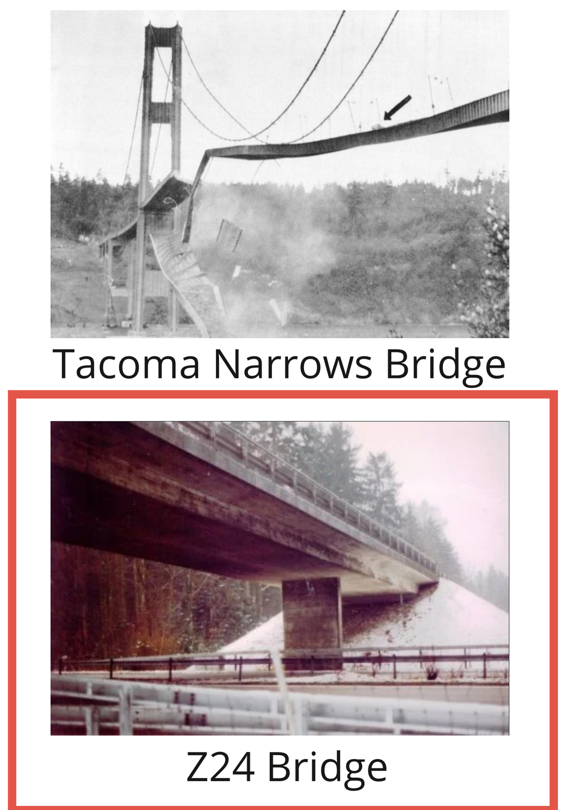
1. Motivation

Lab Experiments | **In-Service Structures**

Toy Models · Steel Frames · Concrete Columns



Tacoma Narrows Bridge

Z24 Bridge

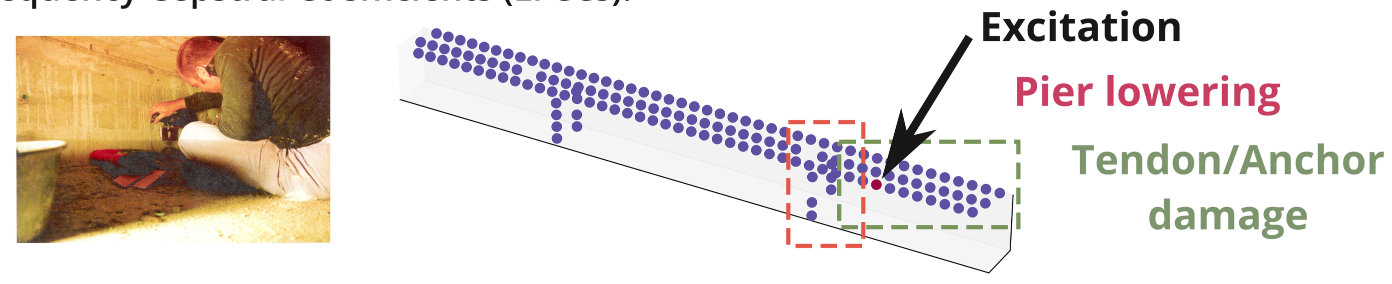
Damage within in-service structures is difficult to observe before failure. Experimentation is well-studied and convenient to examine, but structures in-service are not easily-accessed for testing.

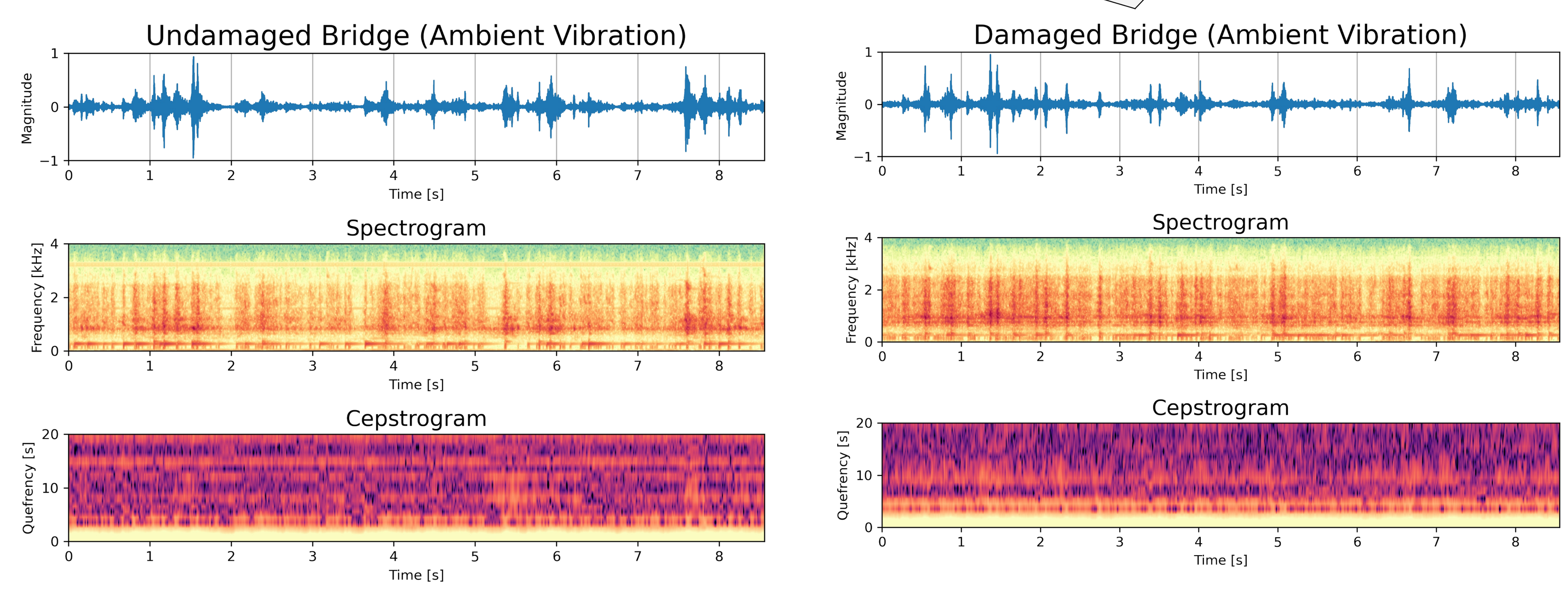
- **Experimental**: 9 Datasets (from LANL, IASC-ASCE, NEES) spanning 60 damage scenarios
- **In-Service**: Z24 Bridge Benchmark with 17 discrete damage scenarios.

Can we detect hidden damage within **in-service** structures via vibration patterns learned from **experimental** testing?

2. Vibration Features

Structural vibrations are measured via accelerometers. Due to the similarity in medium between speech and structural vibrations, we capture potential damage trajectories via **Linear-Frequency Cepstral Coefficients (LFCCs)**.

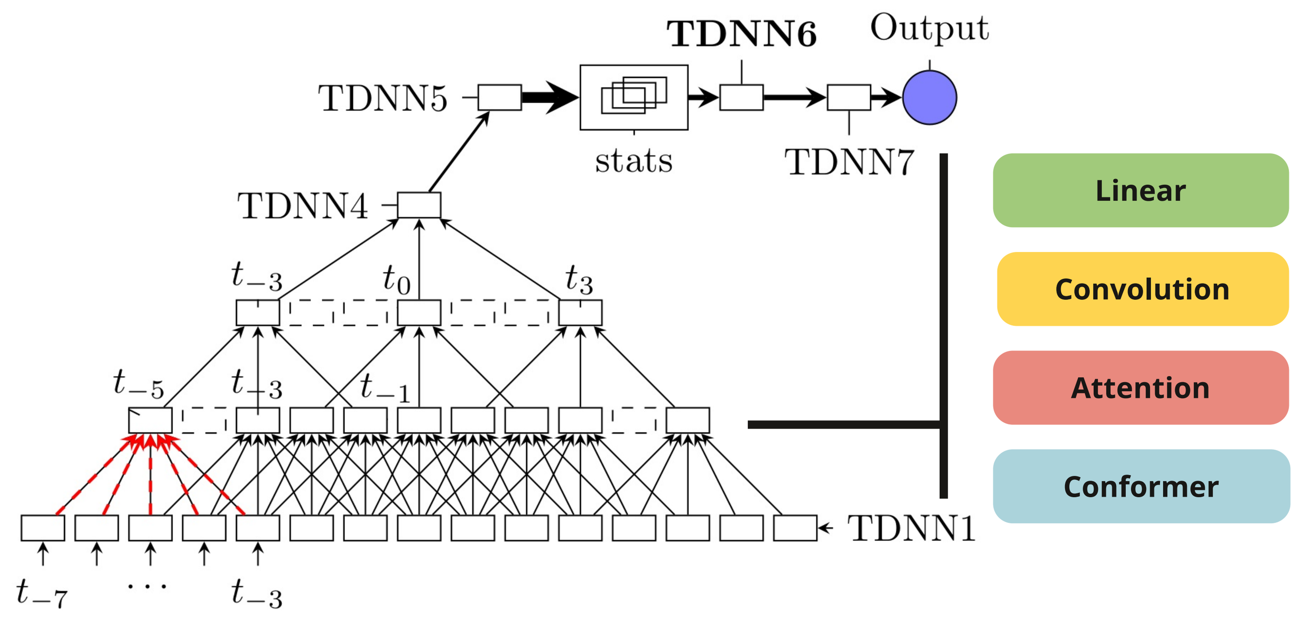


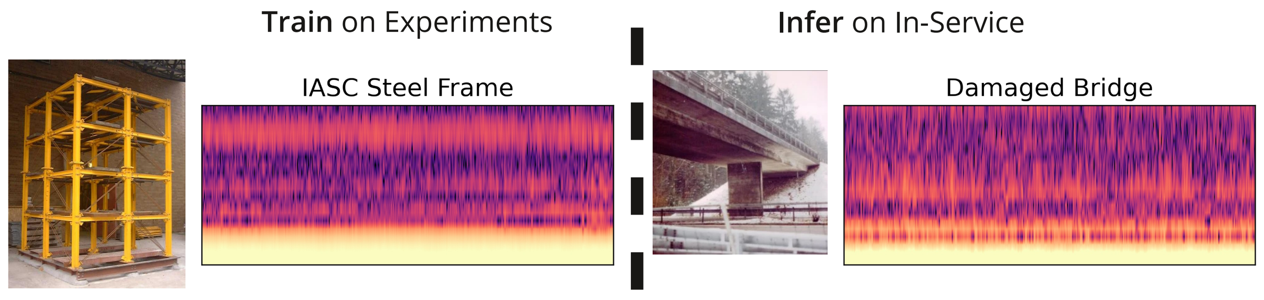


As convolution in time-domain becomes addition in cepstral-domain, **forces stimulating** the bridge are isolated from **changes in structural dynamics**, just as **spoken utterances** are distinguished from **vocal tract dynamics**.

Speech features (LFCCs) applied for identification of **structural damage**

3. Architecture



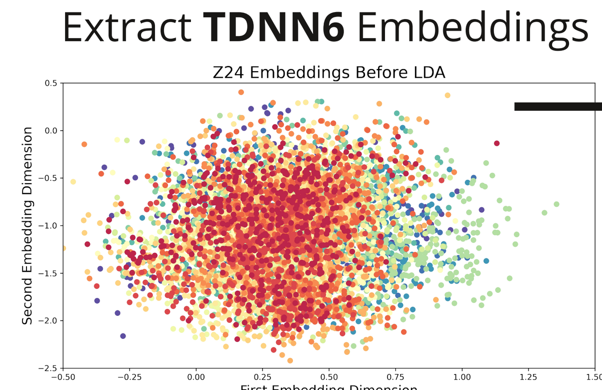


We modify the ***x*-vector** time-delay neural network (TDNN) architecture to capture LFCC trajectories across an accelerometer waveform. We test **various layer mechanisms at TDNN2** to capture damage over wider contexts. Statistics of the TDNN1-5 outputs over the waveform are calculated at the stats layer, and an **output classification head** determines the damage case from **experiments. Embeddings at TDNN6** yield a latent-space representation of **damage**.

TDNN trained on experiments provide **embeddings** as damage representations

4. Generalization

Extract **TDNN6** Embeddings



PLDA model

$$\mathbf{x} = \mathbf{m} + A\mathbf{u}$$

sample: $\mathbf{u} \sim N(\cdot|\mathbf{v}, \mathbf{I})$

from class: $\mathbf{V} \sim N(\cdot|0, \Psi)$

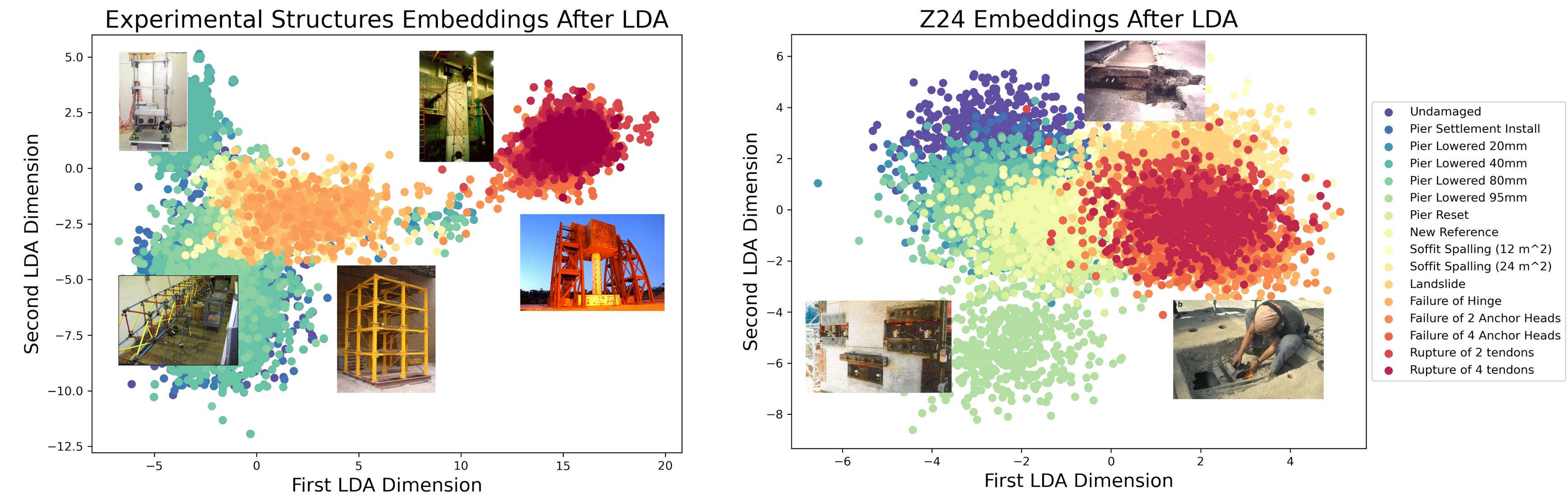
PLDA parameters

$$\mathbf{m} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{x}_i$$

$$A = W^T\left(\frac{n}{n-1}\Lambda_w\right)^{1/2}$$

$$\Psi = \max\left(\frac{n-1}{n}(\Lambda_b/\Lambda_w) - \frac{1}{n}\right.$$

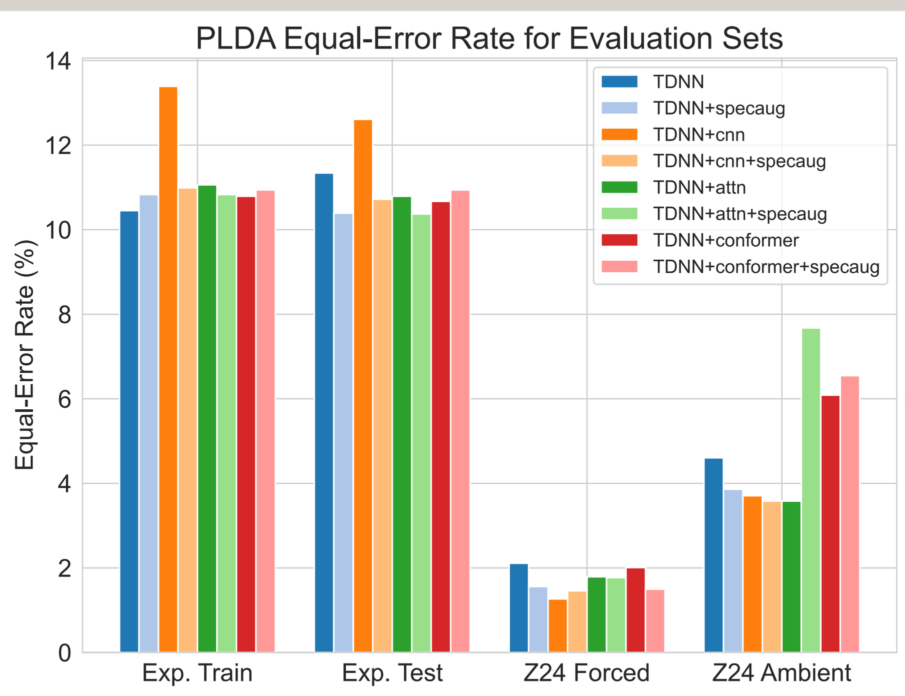
Train on Experiments | **Train** on In-Service

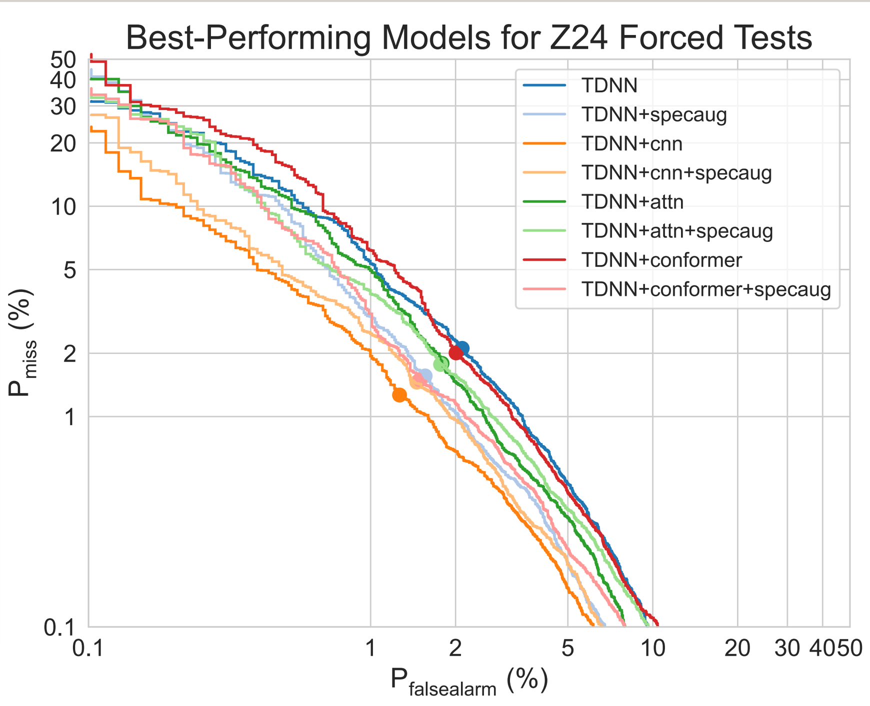


We use a PLDA model to project embeddings from the **TDNN trained on experiments** to potential **damage classes observed from an in-service structure.** We observe sorting of damage heirarchies, such as **structure types in experiments** and **incremental damage progression in the Z24 Bridge.**

PLDA model projects **experimental representation** to **real in-service damage** behavior

5. Results & Discussion

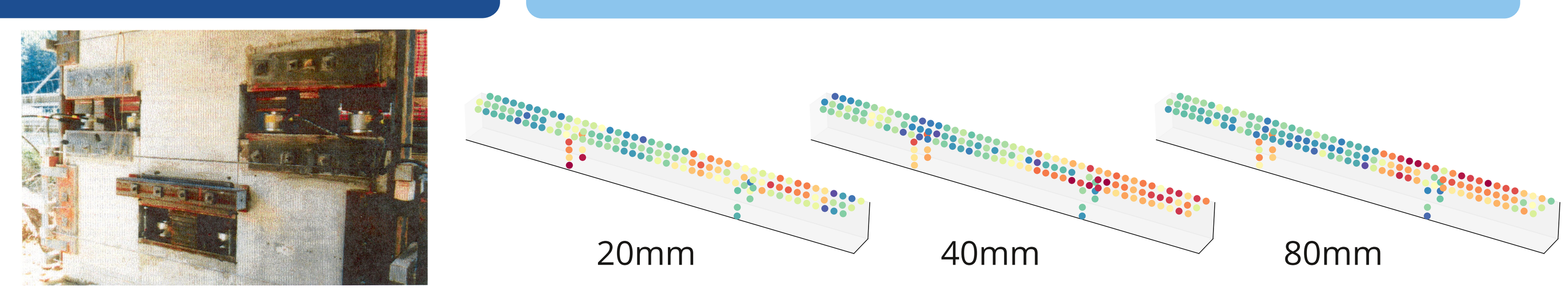




We use **log-likelihood ratio (LLR)** to score accelerometer waveforms belonging to damage cases and **equal-error rate (EER)** to assess performance of **experiments-to-experiments** and **experiments-to-Z24**.classification. We assess over architecture permutations and application of spectral augmentation, with **TDNN+Convolution** yielding our **best-generalizing model. Localization** of Z24 damage over the sensor array is also observed for **effects of damage.**

- **Speaker recognition pipeline** provides framework to **learn structural damage**
- **Generalization and localization of damage behaviors** possible from **experiments to in-service** structures

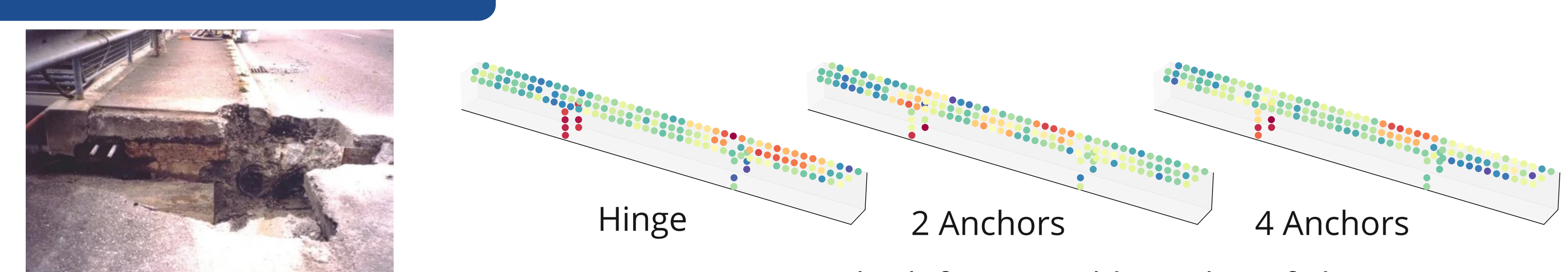
Pier Lowering | **LLR Scores for Correct Class Over Sensors**



20mm · 40mm · 80mm

Span-sagging at right pier

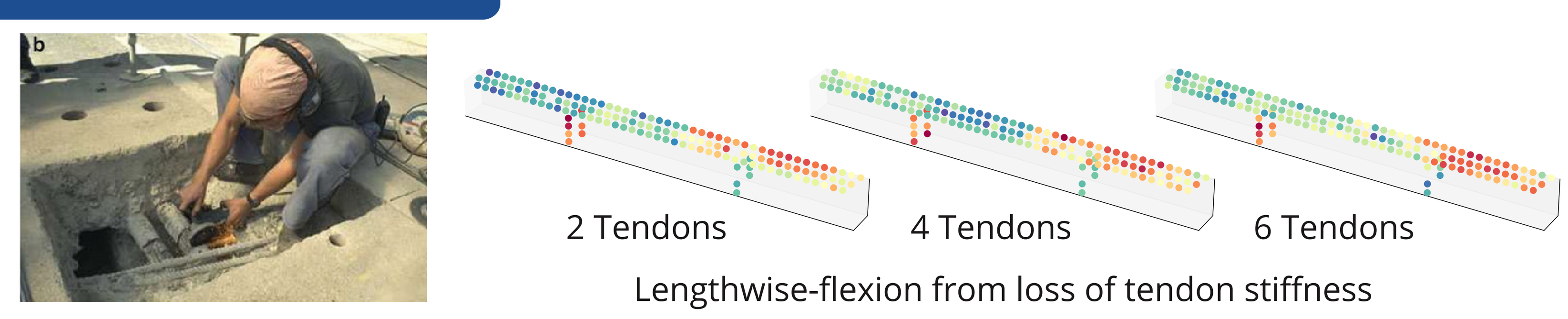
Hinge/Anchor Failure



Hinge · 2 Anchors · 4 Anchors

Torsion-mode shifting as cable-anchors fail

Tendon Failure



2 Tendons · 4 Tendons · 6 Tendons

Lengthwise-flexion from loss of tendon stiffness