Applications of Computer Vision in Structural Health Monitoring

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Presentation Outline

1. **Big Picture of Vision based Structure Health Monitoring**
2. Vision based Automated Visual Inspection of Large-scale Infrastructure
    - Object Recognition based Crack Detection
    - Optimal Design and Identification of Fiducial Markers
3. Vehicle Classification on a Mobile Bridge
4. Conclusion

Big Picture of Vision based Structural Health Monitoring

Processing

- Feature extraction and object detection
- Optimal decision making
- High performance computing

Sensing

- High resolution acquisition in 2D/3D
- 2D photo stitching/blending
- 3D point cloud construction

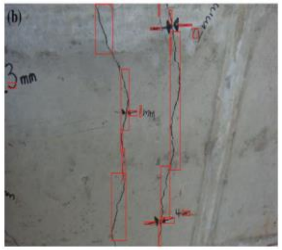
Documentation

- Indexing and searching
- Descriptive metadata schema
- Data visualization

Movement

- High accessibility and coverage
- Communication with sensor network
- Autonomous flying

Previous Research Works



Crack detection and quantification

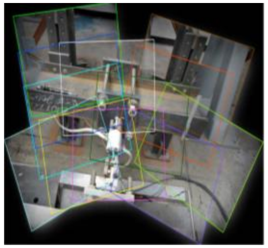
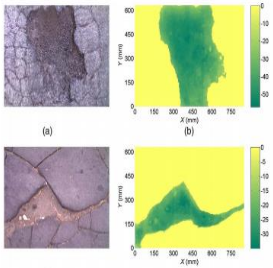
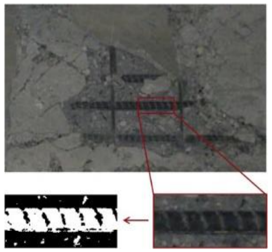


Image stitching for defect detection



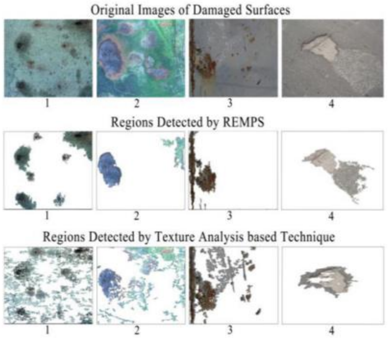
Pavement defect detection and quantification



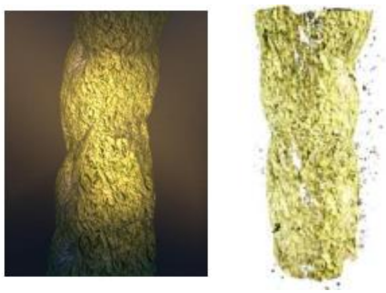
Spalling detection

Post earthquake evaluation

brick counting for façade construction

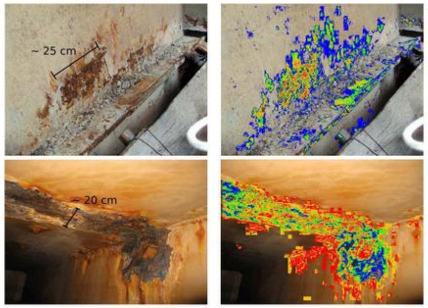


Surface damage segmentation



3D recovery for underwater inspection

Vessel inspection using UAV



Corrosion detection

1 2 3 4

1. Mohammad R Jahanshahi, Purdue University, USA
2. Ioannis Brilakis, Georgia Institute of Technology, USA
3. Michael O'Byrne, Trinity College Dublin, Ireland
4. Alberto Ortiz, University of Balearic Islands, Spain

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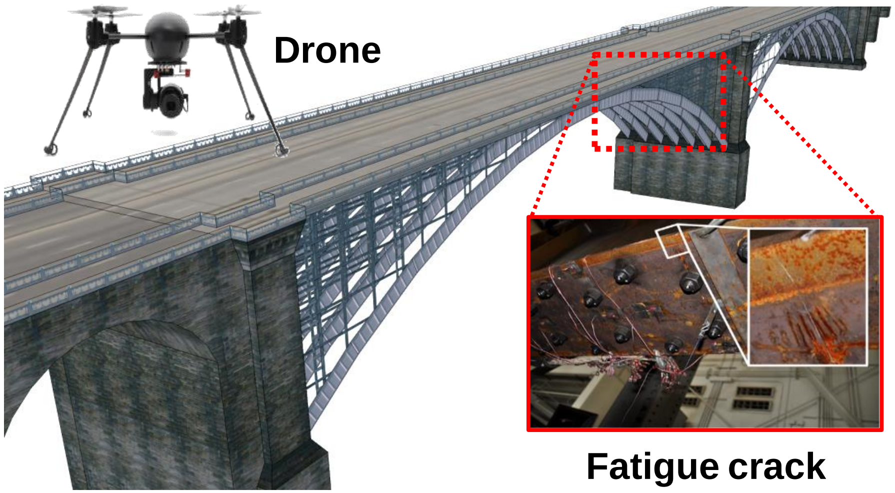
Proposed Approach



Objective

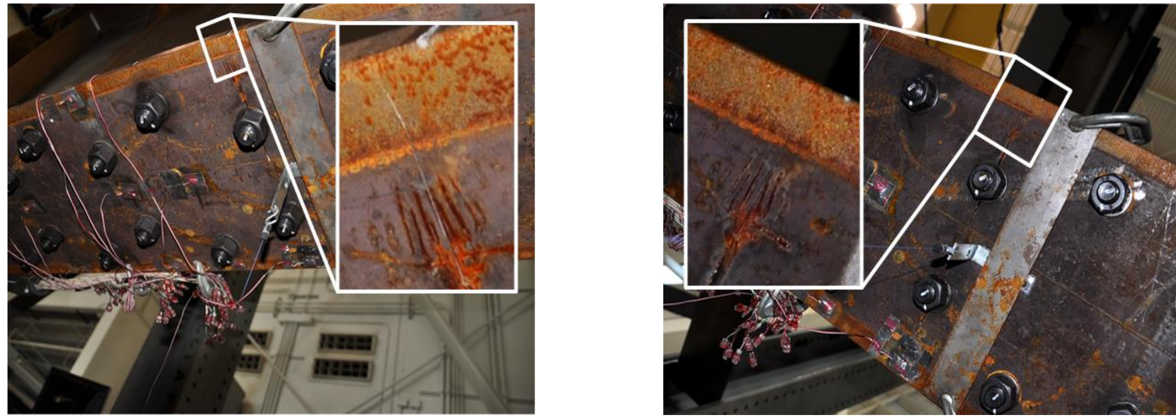
Development of a vision-based visual inspection technique using a large volume of images collected by aerial cameras

Advantage

- **Fully automated visual inspection**
- **Use of images taken under uncontrolled circumstance**
- **Robust detection and minimizing false-positive detection and misdetection**

Problems of Current Vision based Damage Detection

Non-crack area

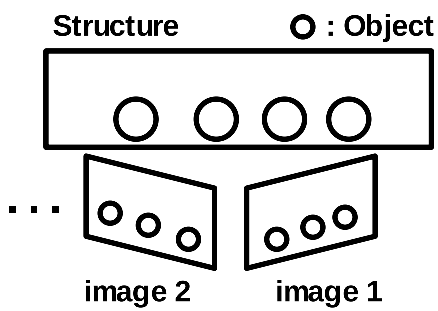


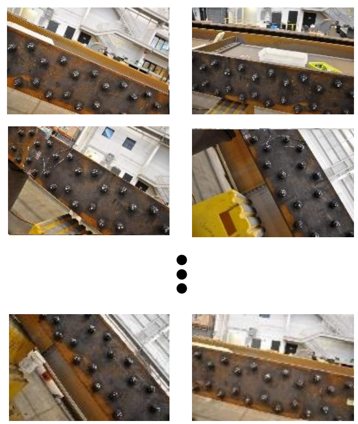
Images of a fatigue crack from different view points

- **Many false-positive alarms and misdetections**
  → Detection of damage-sensitive areas (object)
- **Visibility depending on viewpoints**
  → Use of many different viewpoints of object images

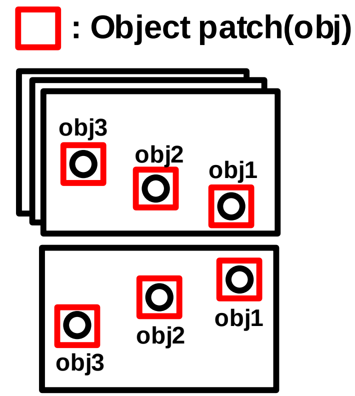
Overview of the Proposed Techniques

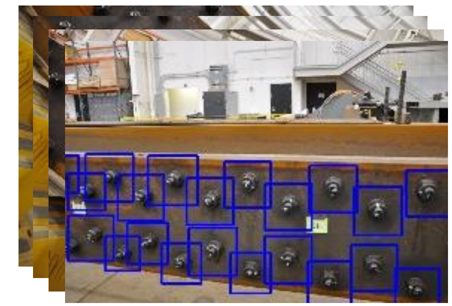
Step 1. Image Acquisition



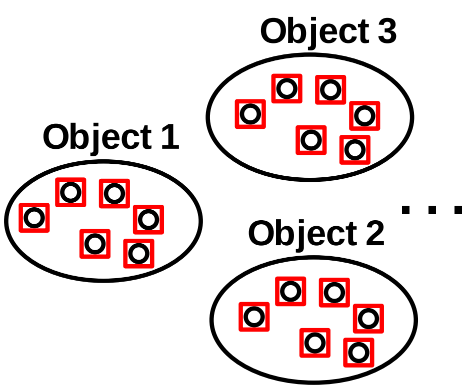


Step 2. Object Detection



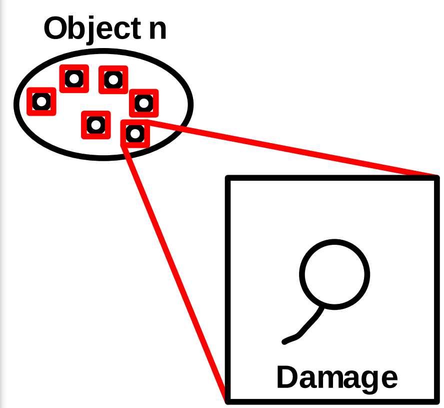


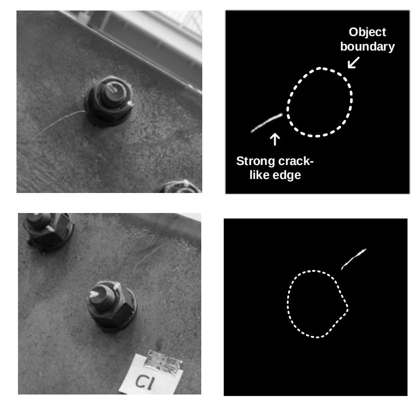
Step 3. Object Grouping



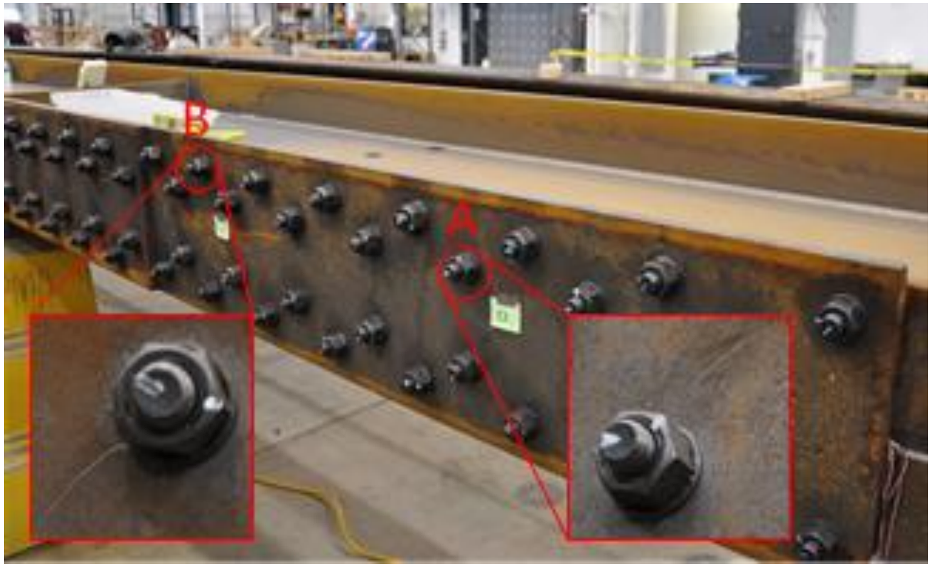
Same bolts

Step 4. Damage Detection

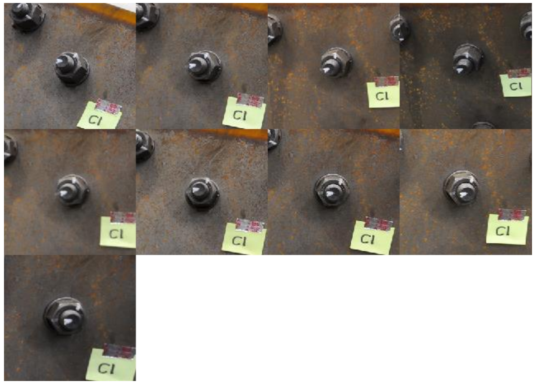




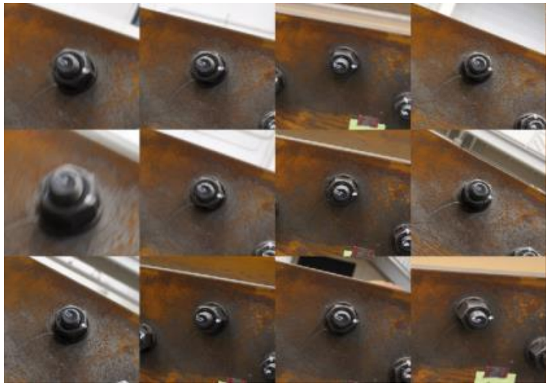
Experimental Setup and Results



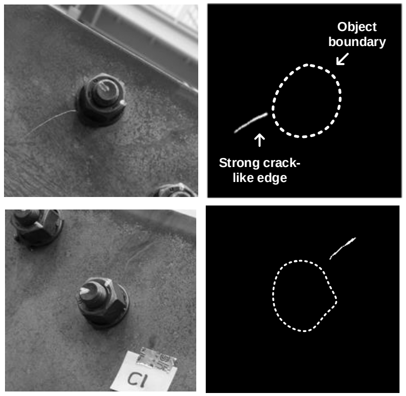
- # of images : 72 (Nikon D90)
- Image resolution : 4288 x 2848
- # of object (bolts) : 68
- # of artificial cracks : 2 (A and B)
- Working distance : 2~3 m
- # of training images : 5 (68 positive and 204 negative image patches)



Location A



Location B



Damage detection

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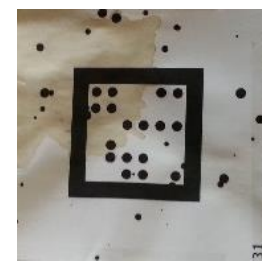
Motivation of Marker-based Structural Health Monitoring

Drone fleets could monitor bridge safety*

In reality

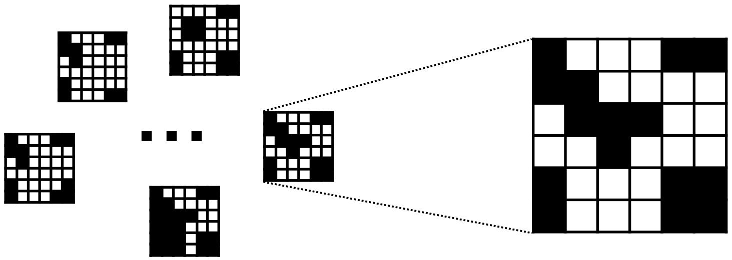
Engineer



Problem: Marker corruption (dirt, torn, shadow, …)

* Reference: http://spectrum.ieee.org/tech-talk/robotics/aerial-robots/drones-could-monitor-bridge-safety
Researchers: Usman Khan (Tufts University), Babak Moaveni (Tufts University)

Proposed Error-correctable Marker Design and Detection

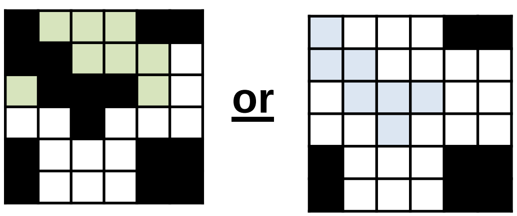


Installed markers

Original
(no corruption)

8bit errors
(black)

7bit errors
(white)



Corrupted markers

- How to design markers for correcting errors
- How to estimate original markers from corrupted markers

Objective

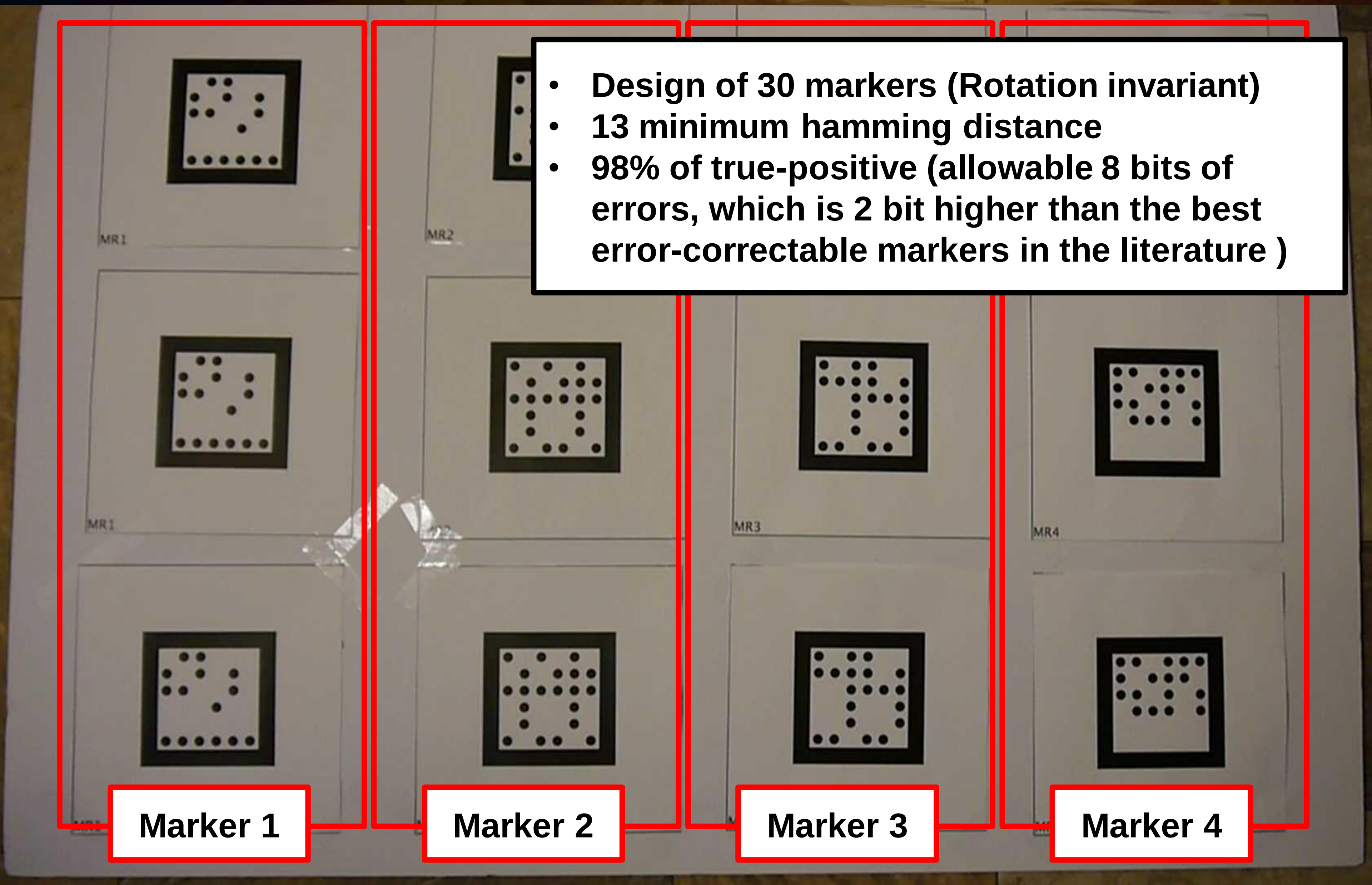
- Error-correctable design and detection of fiducial markers under permanent occlusion (corruption)
- Development of configurable optimal marker design

Contribution

- Advanced error-correctable capability under permanent occlusion (corruption)
- Probabilistic evaluation of error-correctable capability

Demonstration of the Proposed Technique (Video)

- **Design of 30 markers (Rotation invariant)**
- **13 minimum hamming distance**
- **98% of true-positive (allowable 8 bits of errors, which is 2 bit higher than the best error-correctable markers in the literature)**



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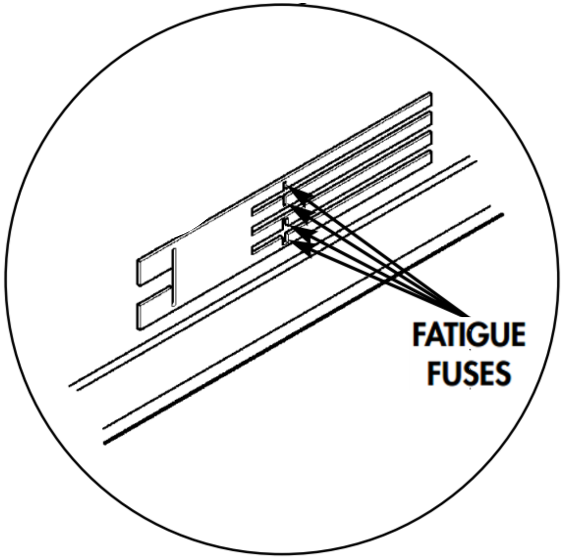
Rapidly Emplaced Bridge (REB)



Remaining Service Life indicators (RSLI)

RSLI has four fatigue fuses; each fuse is designed to break as the bridge incurs an approximate number of crossings (full-load cycles)

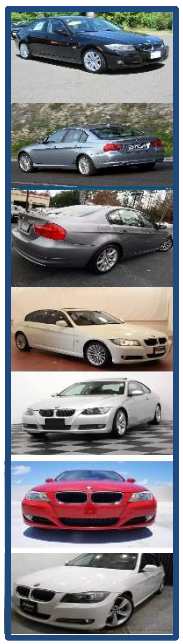
Objective

Development of an algorithm to accurately monitor usage patterns of the bridge, recording the classes of vehicles traversing a mobile bridge

Similarity between Object Image Categorization and Vehicle Classification

Fine-grained image categorization

What class?



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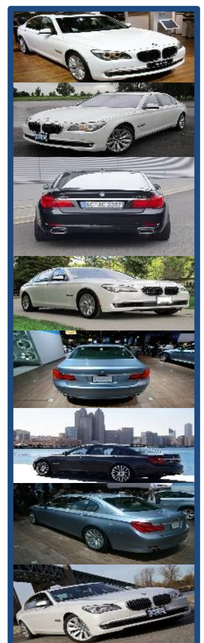
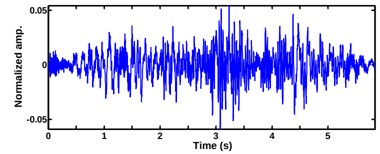


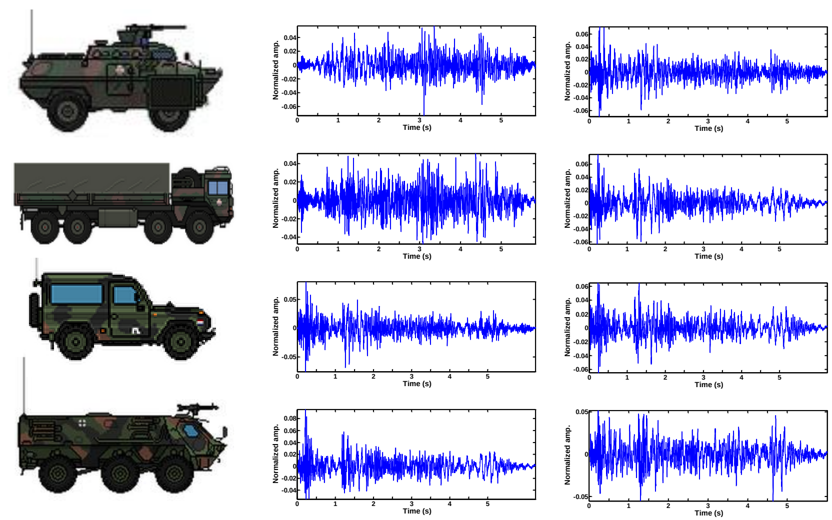
Class 1 **Class 2** **Class 10**

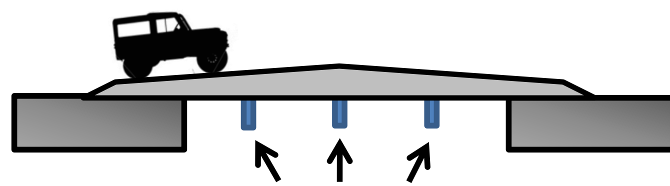
Images from BMW-10 data set

Vehicle classification on mobile bridges



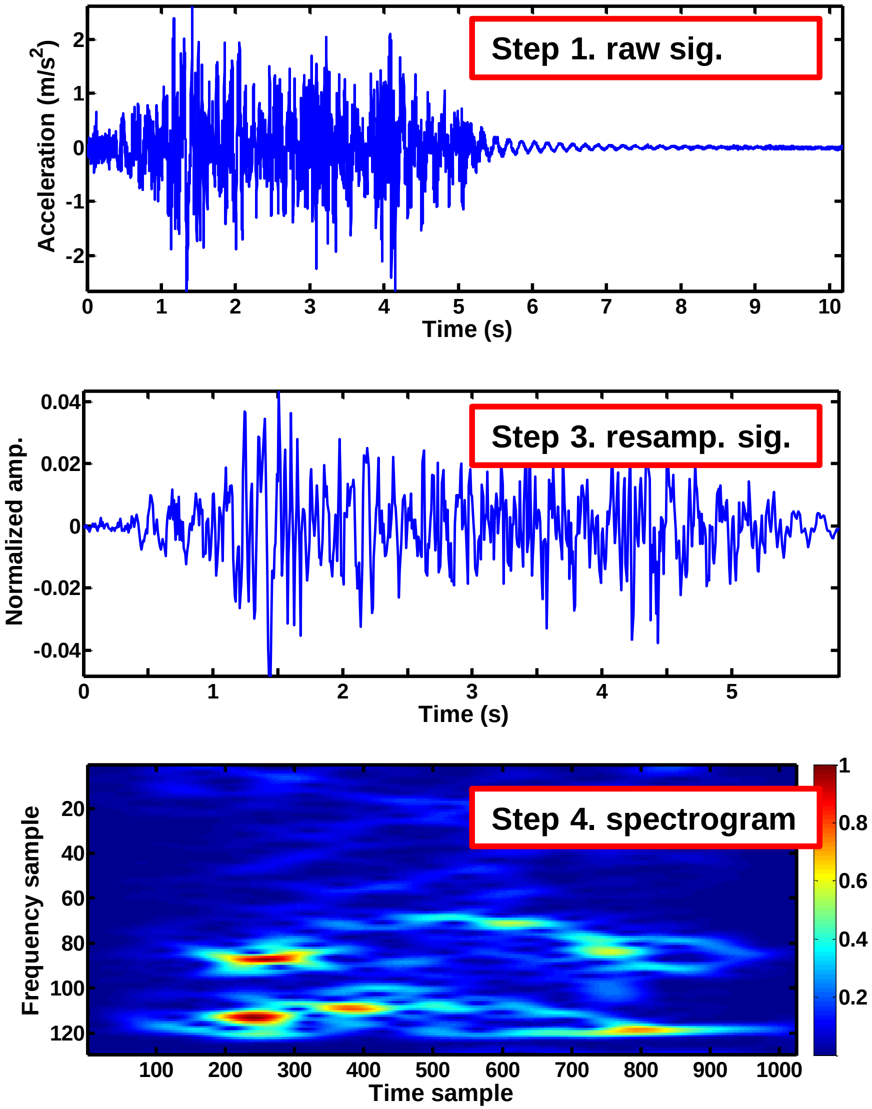
Which vehicle?





Accelerometer

Overview of the Proposed Technique



Training

Step 1. Acceleration signal acquisition

Step 2. Estimation of vehicle exit time

Step 3. Signal resampling

Step 4. Spectrogram computation

Step 5. Integral image computation

Step 6. Feature extraction

Step 7. Learning vehicle classifiers

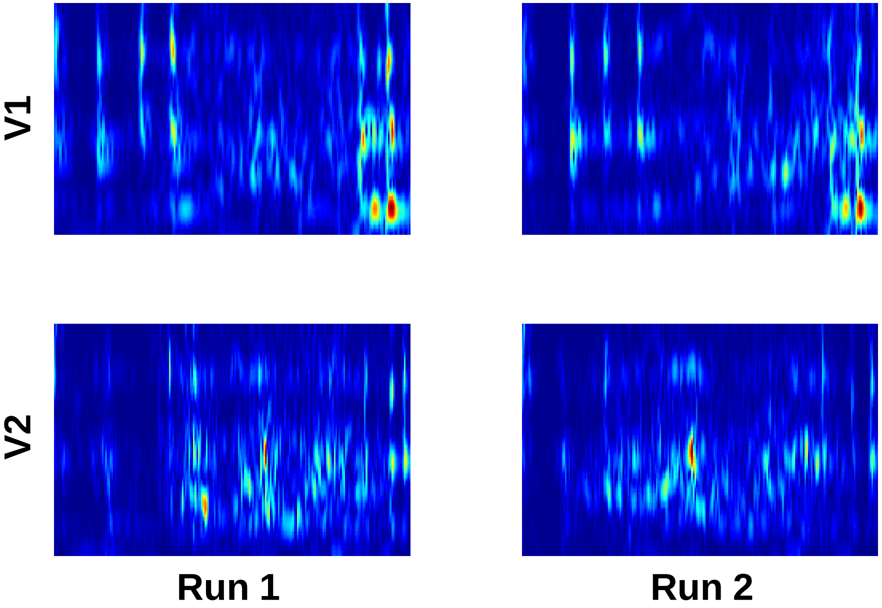
Testing

Step 1. Running 1~6

Step 2. Training data set estimation using a reference vehicle

Step 3. Applying vehicle classifiers learned from corresponding training data set

Preliminary Full Scale Experimental Testing



- Installation of 12 Acc.
- 1024 Hz sampling
- Wood supports and ramps
- Starting from outside of the bridge
- 276 sample data (23 * 12)
  - ✓ V1: 15 runs (slow, middle, fast speed)
  - ✓ V2: 8 runs (slow, fast speed)

Confusion matrix

	Predicted class		
Actual class	V1	V2	Accuracy
V1	15	0	(15/15) 100 %
V2	1	7	(7/8) 88 %

Experimental Setup (Lab-scale)

Bridge installation

B1 (gravel)

B2 (rubber)

B3 (wood)

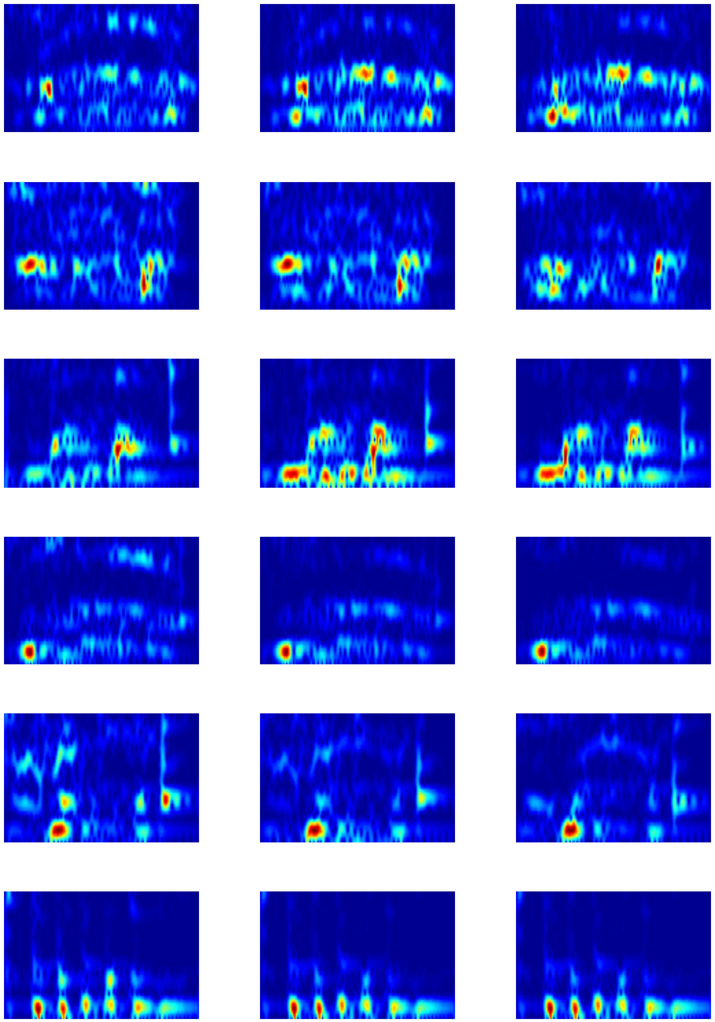
- Installation of 8 Acc.
- 1024 Hz sampling
- Drawing vehicles from three different people
- Starting from outside of the bridge
- 864 sample data (8 x 6 x 3 x 6)
  - ✓ 6 vehicle (V1, V3, V4, V5, V6)
  - ✓ 6 Run (3 forward, 3 backward)
  - ✓ 8 Sensors
  - ✓ 3 Boundary (BG, BR, BW)

Testing vehicles

Experiment Video (Lab-scale)

Vehicle Classification Results (Lab-scale)

V1
V3
V4
V5
V6
V7



Run 1 Run 2 Run 3

Confusion matrix (B1-B1,B2-B2,B3-B3)

	Predicted class						
Actual class	V1	V3	V4	V5	V6	V7	Accuracy
V1	17	0	0	1	0	0	(17/18) 94.4 %
V3	0	18	0	0	0	0	(18/18) 100 %
V4	0	0	18	0	0	0	(18/18) 100 %
V5	0	0	0	18	0	0	(18/18) 100 %
V6	0	0	0	0	18	0	(18/18) 100 %
V7	0	0	0	0	0	18	(18/18) 100 %

Confusion matrix (B1-B1B2,B2-B2B3,B3-B1B3)

	Predicted class						
Actual class	V1	V3	V4	V5	V6	V7	Accuracy
V1	17	0	0	1	0	0	(17/18) 94.4 %
V3	1	17	0	0	0	0	(17/18) 94.4 %
V4	6	0	11	1	0	0	(11/18) 61.1%
V5	7	0	1	10	0	0	(10/18) 55.6%
V6	1	0	2	3	12	0	(12/18) 66.7%
V7	0	0	0	0	0	18	(18/18) 100%

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Conclusion

- Visual data provides crucial and abundant information regarding the condition of a structure, such as change detection,
- Recent advances in the various sensors and sensing systems achieve remarkable visual sensing capabilities in time and space using automated methods. Moreover, The field of computer vision is devoted to such problems of interpreting the world through the analysis of visual images.
- The opportunities associated with automated processing and advanced sensing systems have accelerated the work to develop autonomous visual methods for SHM.
- This study successfully shows implementation of computer vision technology to solve two different problems in SHM.
- It is anticipated that such repurposing of computer vision technology can address many problems in SHM with intelligent ways.

Thanks You


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