# The 2nd International Competition for Structural Health Monitoring (IC-SHM, 2021)

Sponsored by:

- ANCRiSST
- Smart Structures Technology Laboratory, University of Illinois at Urbana-Champaign, USA
- Lab of Intelligent Civil Infrastructure, Harbin Institute of Technology, China
- Zhejiang University/University of Illinois at Urbana-Champaign Institute, China
- Structures and Artificial Intelligence Lab, University of Houston, USA

# Welcome

Civil infrastructure, such as buildings and bridges, constitutes a crucial part of people's everyday lives, pushing strong demand for maintaining its safety and serviceability. These structures are subject to a myriad of risks depending on their age and the environment in which they are built, including deterioration and natural/human-made disasters. To determine an appropriate course of actions against those risks, up-to-date structural conditions need to be assessed by reliable and efficient inspection and monitoring methodologies.

*The 1st International Project Competition for Structural Health Monitoring (IPC-SHM2020)* was organized in 2020 to tackle the challenge by fostering and encouraging innovations in the structural health monitoring (SHM) community. In IPC-SHM2020, 75 teams worked on three projects related to bridges in the field. The projects served as benchmarks to develop and evaluate different structural health monitoring methodologies, leading to the proposals of innovative solutions.

This year, a new competition is launched to further extend the frontiers of computer vision-based civil infrastructure inspection and monitoring. The competition is organized by the Asia-Pacific Network of Centers for Research in Smart Structures Technology (ANCRiSST), University of Illinois at Urbana-Champaign, Harbin Institute of Technology, Zhejiang University/University of Illinois at Urbana-Champaign Institute (ZJU-UIUC Institute), and the University of Houston. All interested students and young scholars are invited to participate in the competition.

The competition consists of three projects: (i) computer vision-based post-earthquake inspections of railway viaducts, (ii) computer vision-based post-earthquake inspections of buildings, and (iii) computer vision-based vibration measurement and damage assessment. Certificates and cash prizes (1st prize - $1000; 2nd prize - $500; 3rd prize - $300) will be awarded for each of the three project competitions. Participants may take part in one or all projects. We will be publishing the IC-SHM 2021 proceedings online, which will include the papers and presentation videos from contest participants. Papers from winning entries will be recommended for publication in the Journal of Smart Structures and Systems, subject to the Journal's peer review process.

We warmly welcome you to the competition and wish you good luck in your efforts!

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University of Illinois at Urbana-Champaign, Urbana, IL, USA

Prof. Hui Li
Chair of IC-SHM, 2021
Changjiang Scholarship Professor
Professor of School of Civil Engineering
Harbin Institute of Technology, China

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| Xiaowei Ye | Zhejiang University, China |
| Jian Zhang | Southeast University, China |
| Dongyu Zhang | Harbin Institute of Technology, China |

# Rules

- Participants must be full-time undergraduate students, M.S. students, PhD students, or young scholars within three years after obtaining their PhD.
- Participation can be by individuals or by teams (each team can have no more than 5 persons).
- Participants can compete in one, two or all three projects.
- Contest entries must include: (i) codes and a readme file that can reproduce your results; We accept code in Python or MATLAB code (2020a or 2020b). Corresponding dataset for reproduction should be submitted as a shareable file link on Google Drive), (ii) a ten-minute presentation video with both the slides and the speaker clearly visible and associated PowerPoint slides, and (iii) a 10-15 pages paper following the downloadable template on the IC-SHM website.
- The papers and presentation videos will be included in the proceedings published on the IC-SHM 2021 website.
- For the promotion of open source in the civil engineering community, participants are requested to make the code for their submission public after the proceeding is published.
- All submitted material should be in English.

# Prizes

- Winners will be selected by the Awards Committee based on the algorithm performance, the video presentation of the results, and the submitted paper (see IC-SHM Evaluation Metrics below).
- First prize (1000 USD cash), Second prize (500 USD cash) and Third prize (300 USD cash) will be awarded for each of the project competitions.
- All participants will receive certificates.

# Publications

- The IC-SHM 2021 proceedings will be published online.
- The winning teams will be invited to contribute full papers for possible publication in a special issue of the Journal of Smart Structures and Systems. Other participants will have opportunity to contribute a paper to the special issue. All papers will be subject to rigorous review.

# Important Dates

| | |
|---|---|
| July 10, 2021 | • Deadline for registration. Participants may register online at https://forms.office.com/r/EuEjUVPTZH by this date. The datasets for competition will be released to the participants after the registration deadline. |
| October 31, 2021 | • Deadline for submission. A link to a cloud folder with all items should be sent to the competition email. For projects with a Kaggle submission, results should also be submitted via Kaggle. More detail can be found in the submission requirements section of this document. |
| December 31, 2021 | • Announcement of competition winners. |

# Contact

- **Websites:**
  http://sstl.cee.illinois.edu/ic-shm2021/
  http://sail.cive.uh.edu/ic-shm2021/
  https://zjui.intl.zju.edu.cn/node/1413
- **Competition e-mail:** ic.shm@yahoo.com

# Computer vision-based civil infrastructure inspection and monitoring challenge using synthetic environments

The goal of the competition this year is to build up on the success of the IPC-SHM2020 and further extend the frontiers of computer vision-based civil infrastructure inspection and monitoring. Driven by the recent advances in computer vision and machine learning fields, an increasing number of researchers have started working on the applications of such approaches to civil infrastructure condition assessment tasks. A challenge is that civil infrastructure condition assessment typically consists of multiple steps, such as data acquisition, data post-processing, and interpretation of the processed data. A process of combining solutions to sub-problems developed independently is not straightforward, or may not lead to a highly effective end-to-end structural condition assessment framework. The competition projects this year seek to provide benchmarks for which students and young researchers in various fields can get together to develop, validate, and distill end-to-end structural condition assessment methodologies in a unified framework.

The competition consists of three projects: (i) computer vision-based post-earthquake inspections of railway viaducts, (ii) computer vision-based post-earthquake inspections of buildings, and (iii) computer vision-based vibration measurement and damage assessment. Each competition project is associated with a dataset created using a 3D photo-realistic synthetic environment that closely replicates civil infrastructure inspection and monitoring scenarios. The first project uses 2,000 viaduct models generated randomly based on the actual design procedure. The second project implements a concept of a physics-based graphics models (PBGM) to generate a synthetic dataset for post-earthquake inspections of buildings, in which surface damage textures are applied to the photo-realistic model of the structure based on finite element analysis results. The third project utilizes the PBGMs to generate a synthetic video dataset of a vibrating structure for development of damage detection approaches. Using the 3D synthetic environments, the entire process of the computer vision-based civil infrastructure inspection and monitoring process can be simulated with the availability of ground truth data, including pixel-wise image annotations. The following sections describe the details of each competition tasks, as well as provided data and the PBGMs used to generate the datasets.

# Project 1: Computer vision-based post-earthquake inspections of railway viaducts

## Background

Civil infrastructure condition assessment using visual recognition methods has shown significant potential for automating various aspects of the problem, including identification and localization of critical structural components, as well as detection and quantification of structural damage. The application of those methods typically requires large amounts of training data that consists of images and corresponding ground truth annotations. However, obtaining such datasets is challenging, because the images are annotated manually in most existing approaches. With the limited availability of datasets, development of effective visual recognition systems that can extract all required information is not straightforward. This project leverages a large-scale synthetic image dataset, termed *Tokaido Dataset*, to develop a system for automated vision-based structural condition assessment of railway viaducts.

The synthetic environments used to generate the dataset consist of 2,000 viaducts with random geometry realized by the actual design procedure. Moreover, random damage (concrete cracks, spalling, and exposed rebar) is imposed to the viaduct columns. The synthetic environments are used to produce a dataset of 8,648 images for structural component recognition and depth estimation, as well as 7,990 images for damage recognition. Example images and ground truth annotations from the dataset are shown in Figure 1. For more information about the dataset, participants are directed to the reference [1].

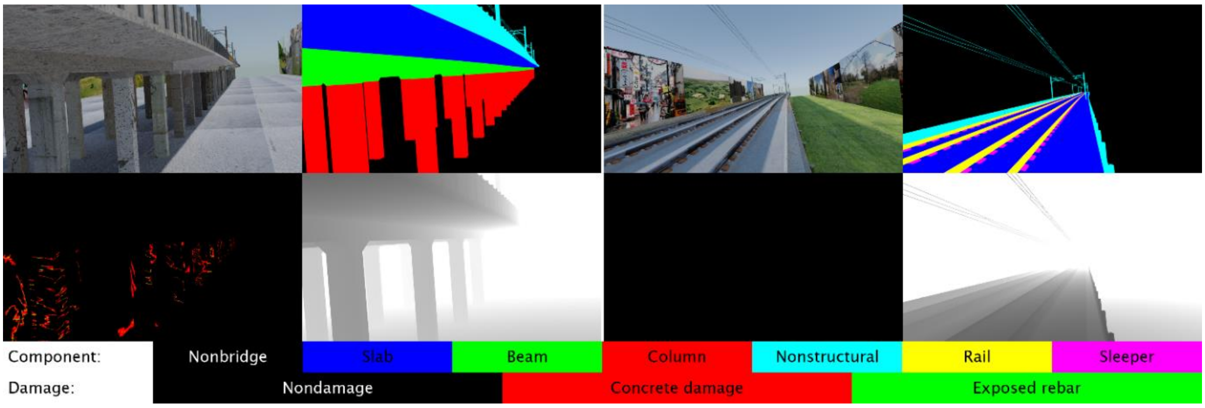



*Figure 1 Example images, structural component label maps, damage maps, and depth maps from the synthetic Tokaido dataset.*

## Data description

Images are rendered assuming UAV-based data collection scenario. Each image is associated with three different sets of annotations: damage, components, and depth map. The depth maps are provided as an optional source of information, and therefore use of the depth maps is not required in this project.

**Project tasks:**

*A python tutorial on semantic segmentation is provided by the committee to help participants with little/no background in deep learning to get started with the project tasks. The participants may feel free to (but are* ***not required*** *to) use the tutorial. Participants are encouraged to develop their own approaches that lead to better performance and/or convenience.*

This project consists of two separate tasks that involve a multi-class semantic segmentation. Participants may participate in either or both tasks. Starter code and a tutorial is provided to guide those not familiar with training neural networks for semantic segmentation. Participants are encouraged to explore different network architectures to improve results.

1. Damage task: Damage annotations including concrete cracks/spalling and exposed rebar pixels.
2. Component task: Component annotations including slab, beam, column, nonstructural, rail, and sleeper.

**Goal & Evaluation**

The provided dataset contains images of 2,000 different viaducts. The participants are provided access to the image data and ground truth for 1,750 of the viaducts (train data) and only the image data for the remaining 250 viaducts (test data). The test data will be released after the commencement of the competition. The objective of this project is to detect and localize structural components and damage to those components.

**References**


[1] Yasutaka Narazaki, Vedhus Hoskere, Koji Yoshida, Billie F. Spencer Jr., and Yozo Fujino, "Synthetic environments for vision-based structural condition assessment of Japanese high-speed railway viaducts." *Mechanical Systems and Signal Processing* 160, 107850, 2021.

# Project 2: Computer vision-based post-earthquake inspections of buildings

**Background**

Visual inspections are widely utilized to assess the condition of civil infrastructure in the aftermath of earthquakes. While careful manual inspections can be time-consuming and laborious, the use of computer vision can help automate several inspection subtasks such as the data acquisition, data processing and decision making. Many researchers have looked to build datasets and deep learning models to better understand the potential of computer vision in achieving the data processing task. The combination of component identification and damage identification can also be used to determine the damage states of components which are important factors towards overall decision making. Additionally, when utilizing robotic data acquisition methods, such as UAVs, a vast number of images can be acquired with little effort. A key challenge for an optimal system is not only determining how to best utilize the acquired data, but also how to acquire data that is most useful. Considering the choice of the robot path together with methods for processing of the data, can lead to more efficient systems that improve reliability of visual inspections.

With field data acquisition, evaluation of the inspection process comprehensively (i.e., data acquisition, data processing, and decision making together) is challenging. This project aims at developing and implementing computer vision-based damage state estimation of civil infrastructure components with the help of synthetic environments. A dataset of annotated images, termed QuakeCity, is generated from multiple simulated UAV surveys of earthquake damaged buildings. One of the critical issues for developing synthetic environments for post-earthquake inspection is how to simulate and subsequently render the damage in the structure due to the earthquake. To this end, PBGMs [1-4] are used to provide a representation of earthquake-induced damage. The procedure is illustrated in Figure 2.

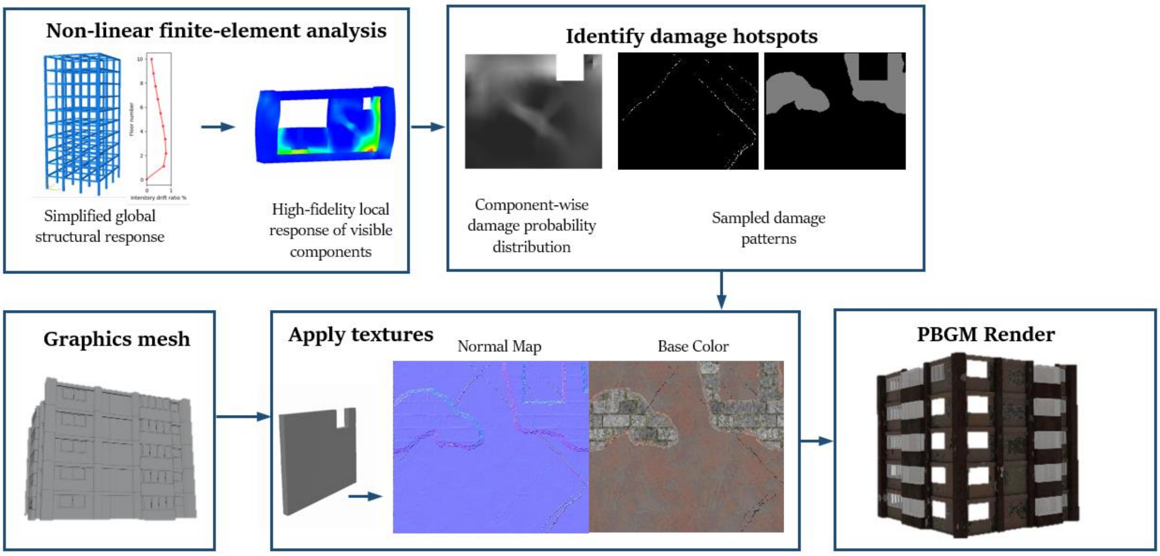



*Figure 2. Procedure for generating PBGMs followed in this competition.*

**Data description**

The QuakeCity dataset is released as part of IC-SHM for project task 2. Images are rendered from multiple simulated UAV surveys of damaged buildings in a city environment. Each survey replicates a field scenario where a UAV circles the building at different altitudes to cover the entire height, width, and length of the building. Each image captured by the simulated UAV is associated with six different sets of annotations including three damage masks (cracks, spalling, exposed rebar), components, component damage states, and a depth map. The depth maps are provided as an optional source of information, and therefore, the use of the depth maps is not required in this project.

**Project tasks:**

*A python tutorial on semantic segmentation is provided by the committee to help participants with little/no background in deep learning to get started with the project tasks. The participants may feel free to (but are* ***not required*** *to) use the tutorial. Participants are encouraged to develop their own approaches that lead to better performance and/or convenience.*

This project consists of three separate tasks. Participants may participate in any or all tasks. All three tasks involve semantic segmentation. A key challenge to be addressed is handling data that is acquired with different views and at different distances from the damaged building. Each task involves images acquired with a multi-distance multi-view test set. Starter code and a tutorial is provided to assist participants with guiding those not familiar with training neural networks for semantic segmentation. Participants are encouraged to explore alternate architectures that can then help improve results.

1. Damage task: Damage annotations for semantic segmentation (pixel-level predictions) with three binary segmentation subtasks.
    a. Cracks
    b. Exposed rebar
    c. Spalling
2. Component task: Component annotations for multi-class semantic segmentation including wall, columns, beams, and windows, window frames, and slabs.
3. Component damage state task: Component damage state annotations for multi-class semantic segmentation include no damage, light, moderate, and severe or NA.

**Goal & Evaluation**

Eleven different buildings are generated for the purpose of this competition. The participants are provided access to the ground truth annotations for 3684 images and only the image data for the remaining 1004 images. The data will be released after the registration deadline to all participants. The objective of this project is to identify the precise location of damage, components, and corresponding damage states by analyzing the image data. An example image is shown in Figure 3. The details of the evaluation metrics are provided in Table 1 at the end of the document.

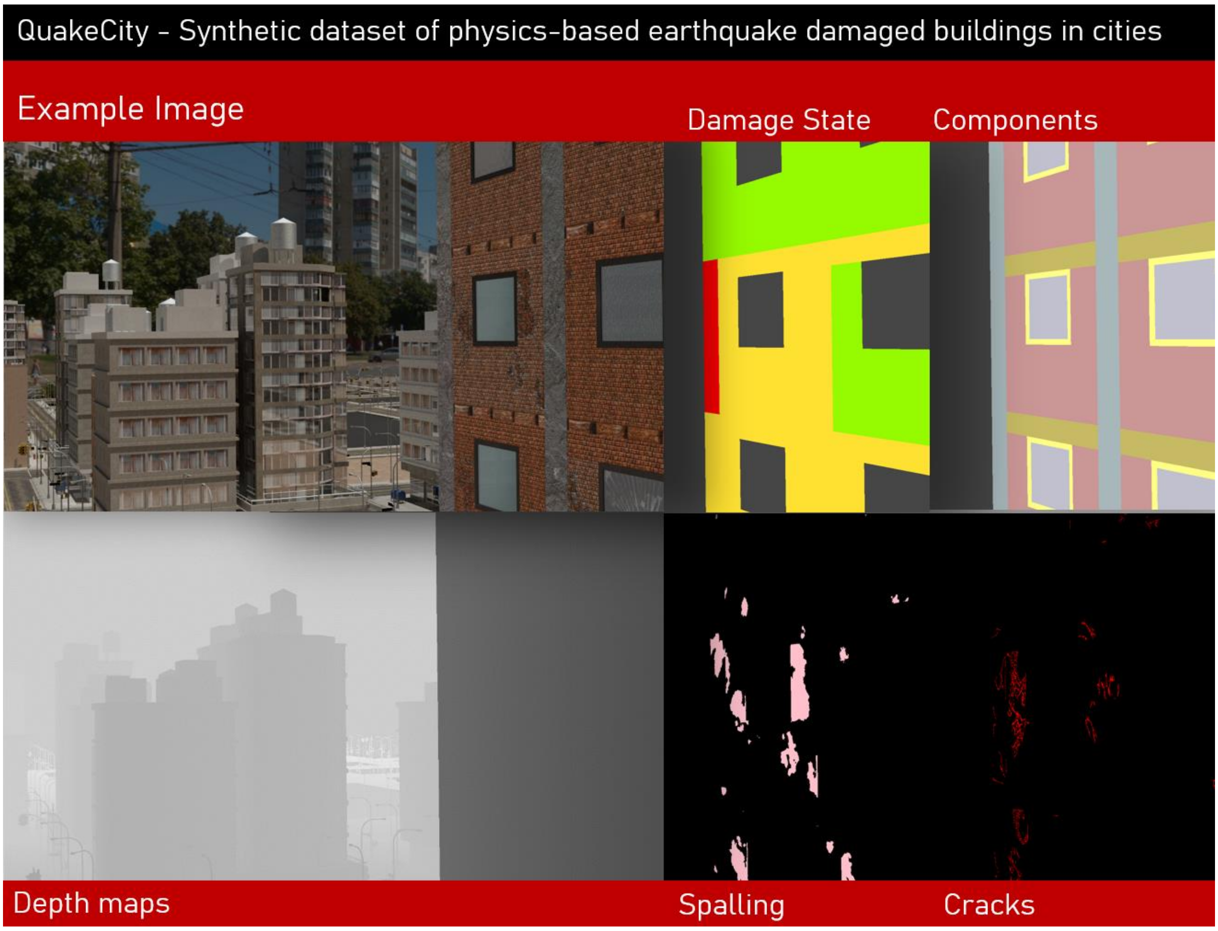



*Figure 3. Example image from Quake city dataset and corresponding annotations.*

**References**


[1] Vedhus Hoskere, "Developing autonomy in structural inspections through computer vision and graphics," University of Illinois at Urbana-Champaign, 2021.

[2] Vedhus Hoskere, Yasutaka Narazaki, Billie F. Spencer Jr., "3D Synthetic Environments with Physics-based Graphics Models for Vision-based Post-earthquake Condition Assessment", to be submitted in July 2021.

[3] Billie F. Spencer, Vedhus Hoskere, and Yasutaka Narazaki, "Advances in Computer Vision-Based Civil Infrastructure Inspection and Monitoring," Engineering, vol. 5, no. 2. Elsevier Ltd, pp. 199–222, 01-Apr-2019.

[4] Vedhus Hoskere, Yasutaka Narazaki, Billie F. Spencer Jr., "Learning to detect important visual changes for structural inspections using physics-based graphics models", 9th International Conference on Structural Health Monitoring of Intelligent Infrastructure, St. Louis, MO

[5] https://sail.cive.uh.edu/quakecity/

# Project 3: Computer vision-based vibration measurement and damage assessment

## Background

Vibration data has been recognized as a useful source of information to assess structural conditions in a non-destructive manner. In particular, the potential of the vibration-based structural health monitoring (SHM) has been strengthened by the advances of computer vision-based approaches for identifying structural deformation. Compared to traditional contact-type sensors, such as accelerometers and strain gages, computer vision-based measurement systems have advantages of less installation costs, as well as the capability of performing area-based measurements, rather than point-based ones. By successful implementation of computer vision-based measurement systems and the effective data post-processing methods, we can expect to improve the reliability and efficiency of the SHM of civil infrastructure.

This project aims at developing an integrated system for the computer vision-based vibration measurement and damage assessment with the help of a PBGM. As shown in Figure 4, the PBGM used in this project is a photo-realistic synthetic model of a truss bridge that deforms based on the finite element analysis results. The attending teams are given synthetic video data of the random (ambient) vibration of the truss bridge under various damage conditions, and asked to detect and localize the damage by a method of their choice. For more information about the PBGM used in this project, the attending teams are directed to a reference [1][2].

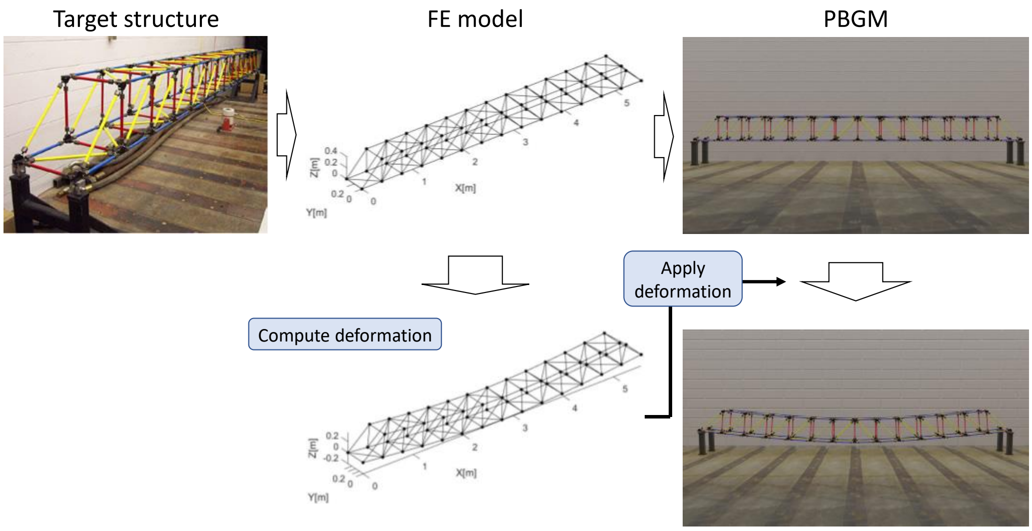


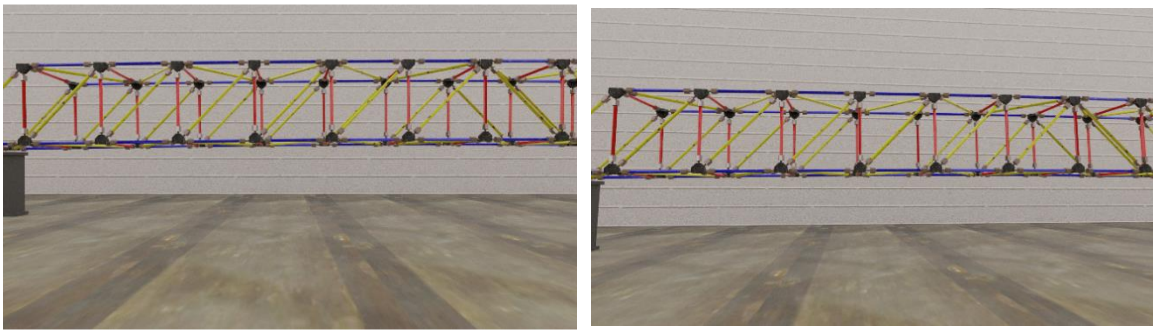

*Figure 4 Physics-based graphics model (PBGM) for computer vision-based vibration measurement and damage assessment.*

## Data Description

The dataset consists of three parts (Table 1):

1. Video data of the truss structure for an undamaged scenario, as well as 10 different damage scenarios. Each video captures the structure's vibration against three-dimensional band-limited white noise excitations applied at all joint locations throughout the duration of the video (excitation is dominant

in the vertical direction). Structural damage is simulated by reducing the stiffness (Young's modulus) of a single member inside the video frames (numbered in Figure 6) by 40% or more. The video data of the undamaged case and the damaged cases 1, 2, 6, 7 are collected in the settings where the image planes are parallel to the truss plane. In contrast, image planes in other damage cases are not parallel to the truss plane, making the task more challenging yet realistic. Example video frames are shown in Figure 5. Furthermore, additional 4 videos are provided: two of them are generated with smaller damage levels and vibration amplitudes, and the other two videos are generated with damage in multiple components. Those scenarios are much more challenging than the cases 1-10, and therefore participants are not asked to work on those cases (the committee will not evaluate the submissions for those cases); those data are provided to aid participants who want to do additional investigations using practically important but exceptionally difficult scenarios.



(a) Undamaged case (b) Damage case 3

*Figure 5 Example frame from the video data.*

2. Simplified design drawing, which contains geometric and material information. The information is accurate but not perfect to mimic the field implementation scenario. For example, the synthetic bridge is cambered, but the design drawing does not give the information of the amount of camber. Note that the geometric and material properties of the synthetic bridge is not necessarily equal to those of the actual structure discussed in [1-4].
3. Ground truth data for damage cases 1-5. The provided data for each case consists of (i) damage location and the amount of stiffness reduction, and (ii) vertical displacement of joints inside the video frames for the first 10 seconds. The ground truth data for the damage cases 6-10 will not be released until the commencement of the competition, and the results for those cases will be used for evaluation.

*Table 1 Structure of the dataset.*

| **Folder** | **File** |
|---|---|
| **Video** | Case_Undamaged.mp4<br>Case_Damaged1.mp4<br>⋮<br>Case_Damaged5.mp4<br>Case_Damaged6.mp4<br>⋮<br>Case_Damaged10.mp4<br>Case_SmallDamage1.mp4 (Optional) |

| | |
|---|---|
| | Case_SmallDamage2.mp4 (Optional)<br>Case_MultiDamage1.mp4 (Optional)<br>Case_MultiDamage2.mp4 (Optional) |
| **Design drawing** | Drawing.pdf |
| **Ground Truth** | GroundTruthData_Damage1.txt<br>⋮<br>GroundTruthData_Damage5.txt |

**Project tasks:**

*A MATLAB tutorial is provided by the committee to help participants with little/no background in computer vision-based vibration measurement and damage assessment get started with the project tasks. The participants may feel free to (but are* ***not required*** *to) use the tutorial. Participants are encouraged to develop their own approaches that lead to better performance and/or convenience.*

1. Using Case_Damaged1.mp4, estimate two-dimensional displacement (unit: pixels) of the truss joint 1-16 shown in Figure 6.
2. Convert the 2D displacement in pixel unit to the vertical displacement in meters.
3. Using methods of your choice, identify natural frequencies and mode shapes of the truss bridge.
4. Repeat 1-3 for the undamaged case. Then, use methods of your choice to identify the location of the damage. Once the ID (Figure 6) of the damaged member is identified, estimate the amount of stiffness reduction (0: no reduction, 1.0: 100% reduction).
5. Perform displacement estimation and damage identification for all 10 damage cases.

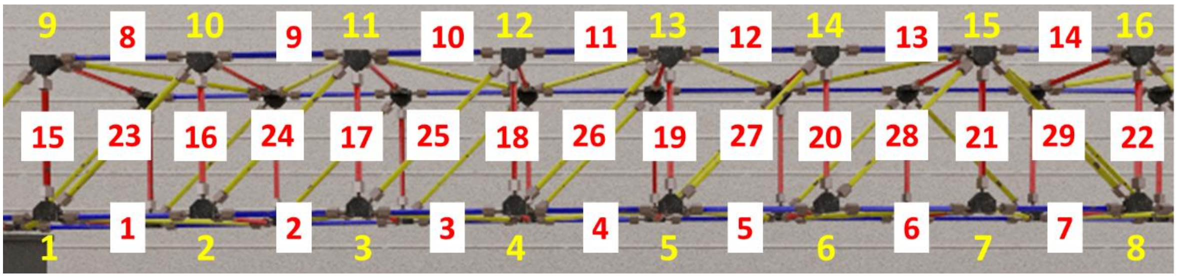



*Figure 6 Truss joint ID (yellow) and member ID (red).*

**Goal & Evaluation**

The goal of this project is to estimate structural displacement accurately from video data, and then identify the existence, location, and severity of structural damage. The project tasks comprise of basic steps of vibration-based SHM that goes from computer vision-based measurements to structural assessment. Through this project, the participants will develop, implement, and validate their SHM systems for the bridge structure.

The committee will first evaluate the displacement estimation and damage localization/quantification results for the damage cases 6-10. The evaluation uses three metrics: displacement estimation error standard deviation, whether the estimated damage location is correct or not, and the absolute error of the estimated stiffness reduction ratio. The submissions are ranked based on the metrics. Then, for the submissions that obtain the highest score, the code supplied by the participants will be used to verify reproducibility. At the same time, the quality of reports containing the discussions about project tasks is evaluated.

**References**

[1] Yasutaka Narazaki, Fernando Gomez, Vedhus Hoskere, Matthew D. Smith, and Billie F. Spencer Jr., "Efficient development of vision-based dense three-dimensional displacement measurement algorithms using physics-based graphics models," *Struct. Heal. Monit.,* p. 147592172093952, Jul. 2020.

[2] Fernando Gomez, Yasutaka Narazaki, Vedhus Hoskere, Billie F. Spencer, Jr., and Matthew D. Smith., "Bayesian inference of structural response of 3D frame structures using localized vision-based measurements", submitted to *Engineering Structures*.

[3] Yong Gao and Billie F. Spencer Jr., "Structural health monitoring strategies for smart sensor networks", Newmark Structural Engineering Laboratory. University of Illinois at Urbana-Champaign., 2008.

[4] Tomonori Nagayama and Billie F. Spencer Jr, "Structural health monitoring using smart sensors". Newmark Structural Engineering Laboratory. University of Illinois at Urbana-Champaign, 2007.

**Competition rules**

To ensure fairness and objectivity, the competition organizers have instated the following rules:

1. Participants may utilize the provided training data to train their model. In addition, the participants may use any publicly available data if they describe the data in the report. Private datasets may not be used.
2. Any external sources of data and code used should be cited.
3. If deep learning methods are used, the test data should not be utilized for supervised training of the model developed by the authors. In other words, the authors should not manually annotate the test images.

**Submission requirements**

| Item | Descriptions |
|---|---|
| Project 1, 2 | The model accuracy score will be determined as follows. Participants will submit their results through Kaggle for the tasks that they will be participating in. A top-down ranking order of submitted models by participants will be given based on the average IoU for the blind-test images. The leaderboard score is the mean of the IoU coefficients for each <ImageId, ClassId> pair in the test set. The links to the Kaggle competition will be sent to all participants via email one month after the start of the competition. |
| Project 3 | The participants will submit txt files of the displacement estimation and damage localization/quantification results by email. They should format the txt files following the template and samples provided by the committee. The participants can refer to readme.txt and Submission_Damage1_sample.txt for details. |
| General requirements | Participants should send to the competition email, a downloadable link to a cloud folder on Google Drive/One Drive/Box/Drop Box/Baidu Cloud, or other similar file sharing platform with the following contents:<br>1. A 10 minute video presentation of proposed method and results, with both the slides and the speaker clearly visible, and associated PowerPoint slides<br>2. A paper-style report that includes the methods, experiments, and results obtained on the training data. The report should be 10 to 15 pages, 11 pt. single spaced excluding references.<br>3. Developed code with comments that will reproduce your results (MATLAB code should be tested in MATLAB 2020a or 2020b; Python code should be tested with Python 3.8.<br>4. All the material necessary to evaluate the model developed by the authors, as well as train the model from scratch, including readme file with instructions and dependencies, and model checkpoint(s). |

**Validation by committee**

1. The submitted test data predictions will be used to evaluate the overall accuracy of the model objectively for each of the four different tasks.
2. For the submissions that obtain the highest accuracy, the code supplied by the participants will be used to verify the model performance.

**Evaluation metrics**

The work submitted by participants will be evaluated by the committee according to **"Identification Accuracy", "Video Presentation"**, and **"Submitted Paper"**. The weights associated with these three parts are shown in Table 1. There will be two stages in the evaluation. The first stage is the preliminary evaluation by the organizing committee. The second stage is the final evaluation by the awards committee.

**Table 1. Evaluation Metrics.**

| Item | Descriptions | Weighting |
|---|---|---|
| Identification Accuracy | The model accuracy score will be determined as follows:<br>For Project 1-2, participants will submit their results through Kaggle. The total score for a project is computed through the total normalized mIoU (TNI). TNI is the sum of sub-task mIoUs normalized by the maximum IoU for the given sub-task. For example, if a project has n sub-tasks, then the $TNI = \sum_i^n \frac{mIoU_i}{\max(mIoU_i)}$. The total scaled weight for a team entry is then given by $\frac{35\times TNI}{max(TNI)}$.<br><br>For Project 3, the committee will evaluate the submissions using the MATLAB code "EvaluateDamageIdentificationResults.m" and compute three metrics: displacement estimation error standard deviation (D), whether the damage localization is correct or not (L), and absolute error of the damage quantification results (Q). Using D, L, and Q, the score of each team for each damage scenario is assigned as follows: (i) +1 if D is in top 50%, (ii) +1 if L is "correct", (iii) +1 if Q is 3rd best, (iv) +2 if Q is 2nd best, and (v) +3 if Q is the best among all submissions. After calculating the total scores for damage cases 6-10, the scores are scaled, so that the score of the best performing team is 35. | 35% |
| Video Presentation | The presentation will be evaluated based on: (i) originality and creativity, (ii) organization of content, (iii) oral delivery, (iv) understanding of research methodology, and (v) clarity of artwork (charts, graphs, slides). | 25% |
| Submitted | The paper will be evaluated based on: (i) adequacy of literature review, | 40% |

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|---|---|---|
| Paper | (ii) organization of content, (iii) innovation and creativity, (iv) research methodology, (v) clarity of figures and tables, (vi) technical conclusions, and (vii) language usage. | |