



Quantifying Earthquake-Induced Displacements of Full-Scale Wood-Frame Buildings using Computer Vision Techniques

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ABSTRACT

In recent decades, a considerable number of publications have been focusing on exploiting quantitative knowledge of the current state of the structure based on measurements by sensors, such as accelerometers, velocity meters, strain gauges, and displacement sensors. However, these vibration-based methods have some drawbacks, including the limited number of sensors for a large structure, expensive installation and maintenance of sensors, complicated data acquisition systems, and limited direct access to the monitoring structure on site. As an adequate solution to the raised challenges, camera and video-based monitoring methods have been proposed as promising tools with unique capabilities of simple instrumentation and remote measurements within varied frequency ranges and spatial resolutions for multiple points of the structure. This paper presents an experiment in which a fixed camera is used to track the motion of a full-scale wood-frame school building subjected to an earthquake. Feature tracking method was employed to analyze the captured videos in the experiment. This method entails identifying specific elements or points on the structure, such as corners or markers, and tracking their movement over time. The experiment aims to showcase the validity of computer vision in measuring displacement precisely and to compare the results with those obtained using a traditional displacement measurement technique, such as a string pod attached to the edge of the structure. The comparison showed that the displacement results obtained using computer vision matched well with those obtained using the string pod. This demonstrates the effectiveness of computer vision in accurately measuring displacement and highlights its potential as a valuable tool in the field of structural engineering.

Keywords: computer vision, displacement measurement, feature tracking, wood frame structure, earthquake.

INTRODUCTION

All existing structures, such as buildings, bridges, dams, tunnels, et cetera., are exposed to damage with different intensities and locations during their operation due to the various phenomena they encounter. This can disrupt their functionality, causing future deterioration and risk of asset failure. Researchers focus on identifying, localizing, and quantifying bridge damage early and quickly after earthquake excitation. This section aims to provide an overview of some of the most noteworthy advancements in using images to assess earthquake-damaged structures and detect major structural failures.

Computer Vision, initiated in the 1960s, attempts to imitate humans' phenomenal perception process in a machine. The early approaches to this technology were detecting lines and fitting simple geometric blocks to these lines to understand the world such that a robot can act in it [1]. After a decade, some progress was made regarding taking a scene and partitioning it into different segments. In the 80s, there was a shift toward using Neural networks (NN) and self-driving cars. Over the past few years, artificial neural networks have significantly contributed to the computer vision field. It is becoming increasingly common to use CV applications to detect objects, recognize faces and people, segment images, reconstruct images, estimate poses, and track visuals in real-time.

There have been many advances in vision and computer science in recent years, which researchers have utilized to determine whether an earthquake has damaged the bridge and whether it still functions and is safe to cross. Dong has introduced a comprehensive review of CV-SHM concepts, approaches, challenges, and opportunities in assessing, managing, and maintaining real-life civil structures at the local and global levels [2]. A structure's condition can be evaluated locally, such as cracks, spalling, corrosion, rusting, and delamination, and globally, such as displacement, strain/stress, modal parameters, cable force, and external load, by using its image content. An overview of CV-based structural health monitoring assessment is shown in Figure 1. Measuring and inspecting are separate processes. The first one analyzes images to determine the damage extent and structural components. Suppose no collapse has been identified at the system level. In that case, the damage type and location can be obtained from the critical supporting elements. In the second process, researchers use digital video or image sequences to monitor structural responses such as displacement and strain to get the dynamic properties of structural systems. The use of acceleration is widespread since it is cost-effective and convenient in terms of installation to measure the structure's dynamic response, but it is typically inaccurate at low frequencies. Alternatively, displacement allows for more accurate measurements at lower frequencies.

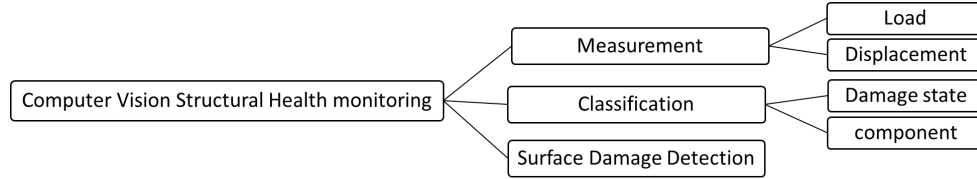


Figure 1 Overview of the CV-based SHM assessment framework

In this study, the accuracy of using computer vision in measuring the displacement of a full-scale wood-frame school building subjected to an earthquake is investigated. Specific features on the structure are tracked using a commercial photogrammetric software and a fixed camera. The effects of target size and the use of natural and artificial targets on the accuracy of the displacement measurements are also investigated. The results obtained using the Canon TSI camera are presented in this conference paper, while the effects of camera movement, different camera resolutions, and distances will be discussed in a future publication.

DISPLACEMENT MEASUREMENT

Background

A second approach to the application of CV in the SHM domain is to perform vibration testing using optical methods. An in-depth look at optics-based deformation tracking technology is provided by XU and Brownjohn [3]. Vision-based displacement measurement methods have mainly been developed for acquiring video frames, tracking selected targets or virtual markers in image sequences, and then converting them to the time history of structural displacement. Derived structural motion information can be used to calculate dynamic properties of structural systems, such as modes, frequencies, and damping, using a classical modal analysis [4].

The primary step in vision-based vibration monitoring is to calibrate the camera so that the physical object in the real world (three-dimensional) can be projected into the image plane (two-dimensional). A transformation matrix is calculated in this step in order to convert pixel-based displacements to engineering-based displacements (millimetres). There are currently three popular camera calibration methods: scale ratio, planar homography matrix, and full projection matrix. Scale ratios can be calculated much more quickly by dividing the camera-to-target distance by the camera's focal length, but they require that the camera's principal axis be perpendicular to the target surface. Homography can be used as an alternative if the target does not exhibit out-of-plane motion [5]. Implementing full projective transforms for solving the camera angle and radial distortion problems is based on estimating extrinsic and intrinsic matrices. An intrinsic parameter of the camera is related to its lens characteristics, while the extrinsic parameter refers to its position. The camera calibration method developed by Zhang requires the camera to observe a planar pattern from four different orientations [6] and is widely used in popular software packages such as Matlab Computer Vision Toolbox and the open-source Python library called OpenCV.

The next step is to select the region of interest (ROI) or target that identifies the location where the object needs to be tracked. There are two main categories of targets: artificial features (including markers, LEDs, and planar panels with patterns[7]) and distinctive structural features (for instance, bolts or holes [8]). These features need to have a well-defined position in the image and remain stable to variations in photometric (illumination) and geometric (motion, scale changes and rotation). As the next step towards achieving displacement extraction, we need to track the target locations in a video recording using visual tracking algorithms, such as template matching, feature matching, optical flow, and geometry matching.

Template matching aims to calculate the similarity between a predefined sub-image called a template and all possible locations in the image. This process is done once the template sweeps the photograph entirely. Digital image correlation (DIC) and tracking is a vision-based measurement technique for extracting 2D and 3D full-field shape deformation or strain data under a well-controlled laboratory environment for experimental mechanics and material testing. It is generally used to match and track data throughout time for static or quasi-static purposes and differs slightly from template matching[9]. Feature matching involves identifying interest points, extracting descriptive information about them, and matching them on the basis of predefined distance functions. Interest points, also called feature points, are distinct patterns found in the image, such as blobs, edges, corners, grayscale intensity, colour, and geometrical shape. In general, descriptors combine the location, intensity, gradient, and orientation of the region where the feature point resides. A distance measurement verifies the similarity between feature descriptors[10]. The optical flow concept analyzes the relative motion of all pixels across different frame sequences based on their velocity of movement and brightness variation. Various algorithms are available for estimating optical flow, including differential, region-based, energy-based, and phase-based approaches [11]. In geometry matching, different types of target patterns are manually used, such as line-type, circular-shaped, cross-shaped, or custom-made targets. The algorithm and criterion for matching and the strengths and weaknesses of common visual tracking approaches are summarized in Table 1.

Table 1 Summary of the displacement measurement methodologies

Tracking	Criteria/ strengths & weaknesses	Algorithms		
Template matching	Similarity Measurement criteria •Correlation Coefficient •Cross-correlation •Normalized Cross-correlation •Normalized Correlation Coefficient Strengths/Weakness •Simple •Unreliable in field conditions due to shading, illumination, and background	•SSD & SAD •OSSD & OSAD •ZNSSD & ZSAD		
Point matching	Similarity Measurement criteria •Euclidean distance •Hanning distance Strengths/Weakness •Less sensitive to changes in illumination, shape, or scale •required manual adjustment	detector & descriptor • SIFT • SURF • ORB • Haris corner • Shi-Tomasi corner • BRISK • VGG • FAST • FREAK		Matching •Brute-Force matcher •KNN •FLANN Outlier removal •RANSAC •LMS
Optical flow	Strengths/Weakness •Target free •Fast, accurate results in controlled environments	• LK • HS • BA	• CLNL • Phased-based • CNN-based (FlowNet and FlowNet2)	
Geometry matching	Strengths/Weakness •Manual target dependant •Less sensitive to changes in illumination, shape, or scale •Simple computations	Image processing •Brightness thresholding •edge detection •corner detection		
Sum of Square Difference (SSD), Zero-mean Normalized Sum of Square Difference (NSDD), Sum of Absolute Difference (SAD), Optimized Sum of Absolute Difference (OSAD), Oriented Fast And Rotated Brief (ORB), Scale-Invariant Feature Transform (SIFT), Random Sample Consensus (RANSAC), Visual Geometry Group (VGG), Linear Median Square (LMS), Lucas-Kanade (LK), Horn & Schunck (HS), Black & Anandan (BA), Classic+NL (CLNL), Fast Library for Approximate Nearest Neighbors (FLANN), Binary Robust Invariant Scalable Keypoints (BRISK), Speeded Up Robust Features (SURF)				

In this article, the ProAnalyst software (provided by Xcitex Inc.) was used to track the features of a full-scale wood frame structure subjected to earthquake shaking. The software provides a range of tools for capturing and processing video data, including feature tracking, which uses advanced point matching algorithms to track the movement of specific points or features within an image or video sequence. The software also offers various methods of calibration, including single-camera and multi-camera calibration, to establish camera positions and orientations for accurate measurement. In addition, ProAnalyst uses computer vision techniques to measure displacement and deformation, which is critical in assessing structural integrity and safety. One of the major benefits of using ProAnalyst is its user-friendly interface, which does not require coding expertise, allowing engineers to focus on analysis rather than programming [12].

TEST SETUP

This study aimed to analyze the displacement of a full-scale wood-frame school building during an earthquake using computer vision. The experimental setup involved modeling a two-story school building with dimensions of 7.6 meters by 6.1 meters for the floor plan and a height of 3.2 meters for each story. To simulate the second story, six steel inertial plates weighing 3600 kg each were placed on top of the first story. The earthquake used in the experiment was a one-direction shaking table test at the Earthquake Engineering Research Facility (EERF) of the University of British Columbia (UBC), which replicated 50 percent of the Tohoku earthquake with a magnitude of 9.0 and a duration of six minutes. Figure 2 displays the layout of the building.

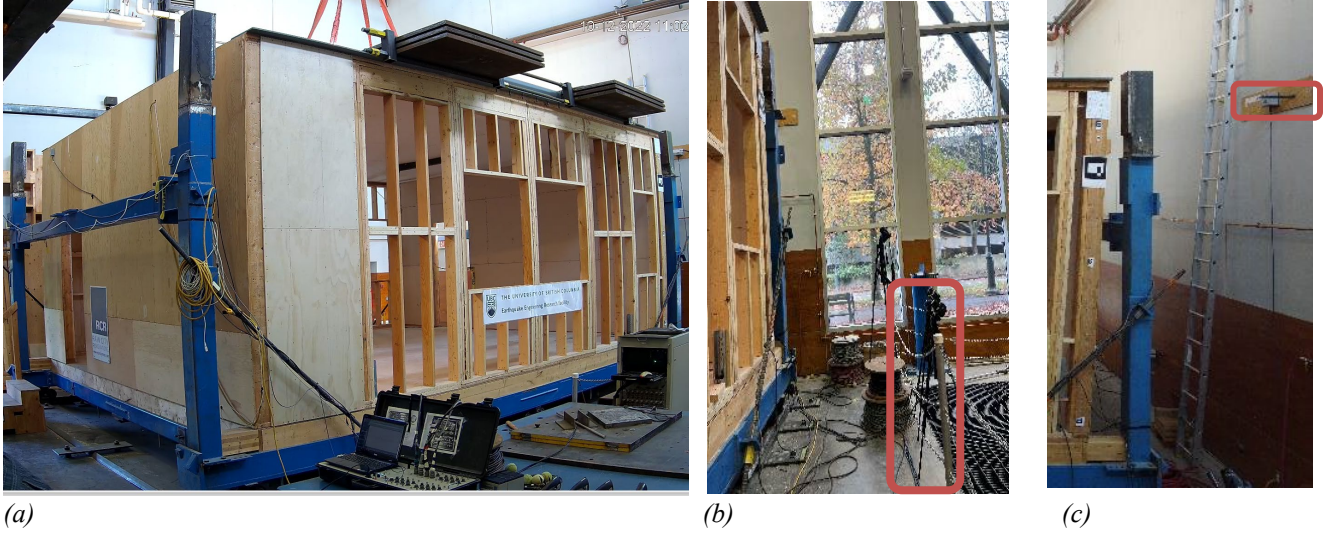


Figure 2 Experimental arrangement a) Layout of the full-scale wood-frame school building b) camera setup c) string pod location

The motion of the structure was captured using a fixed camera placed at a distance of 230 cm from the structure with an angle of 40 degrees to the horizon. The Canon EOS Rebel T5i, used for this experiment, is capable of capturing high-resolution images and videos, featuring a 18-megapixel sensor, full HD video recording. The camera was set to capture only the top right corner of the specimen, as shown in Figure 2. The frame rate of the captured videos was 60 frames per second, and the resolution of the videos was 1920 by 1080. This high-quality video footage allowed for precise tracking of the motion of the structure using ProAnalyst software. In addition to the camera, the structure was equipped with different accelerometer and string potentiometer sensors. The string potentiometer was attached to the west end wall of the structure.

To investigate the effect of target size on the accuracy of the displacement measurements, different targets were attached to the right top corner of the building as illustrated in Figure 3. These included a page with different circle targets on it and ArUco targets with different dimensions, including 5 by 5, 20 by 20, and 2 by 2. Both natural targets, such as holes on the studs or corners, and artificial targets were used, and their accuracy was compared to that obtained using a traditional displacement measurement technique, such as a string potentiometer attached to the edge of the structure.



Figure 3 target placement on the specimen

DETAILED MODEL IN PROANALYST

ProAnalyst is a powerful software tool designed for users who want to perform precise feature tracking on video data. This software offers a range of features and tools that enable researchers to calibrate the camera, process the image, filter the data, track features, and configure the output data. The ability to accurately track the movement of specific points or targets in a video provides valuable data for a variety of engineering applications, especially when analyzing the performance of structures subjected to dynamic loading such as earthquakes or wind events.

The first step in the feature tracking process is to calibrate the camera using one of the several available methods, including normal, multiple, and perspective. The normal method, also known as the pinhole camera model, assumes that the camera is a simple pinhole camera with a single viewpoint. The multiple method, also known as the fisheye model, is used for cameras with wide-angle lenses that produce significant distortion. Finally, the perspective method, also known as the thin-lens model, is a simplified version of the pinhole model that assumes that the lens is thin and that light rays pass through the center of the lens. It is important to know the dimensions of the targets and window frame to convert from pixel units to physical units, typically centimeters. The calibration algorithm estimates the camera parameters in pixel units, but to use the camera for measuring real-world distances, pixel units must be converted to physical units using a known scale factor. By inputting the dimensions of the targets and window frame, the camera can be calibrated in physical units, enabling it to measure real-world distances accurately. To perform the calibration, four points on the edge of the calibration target and the window opening in the image are selected, and their actual XY coordinate are inputted as shown in Figure 4.

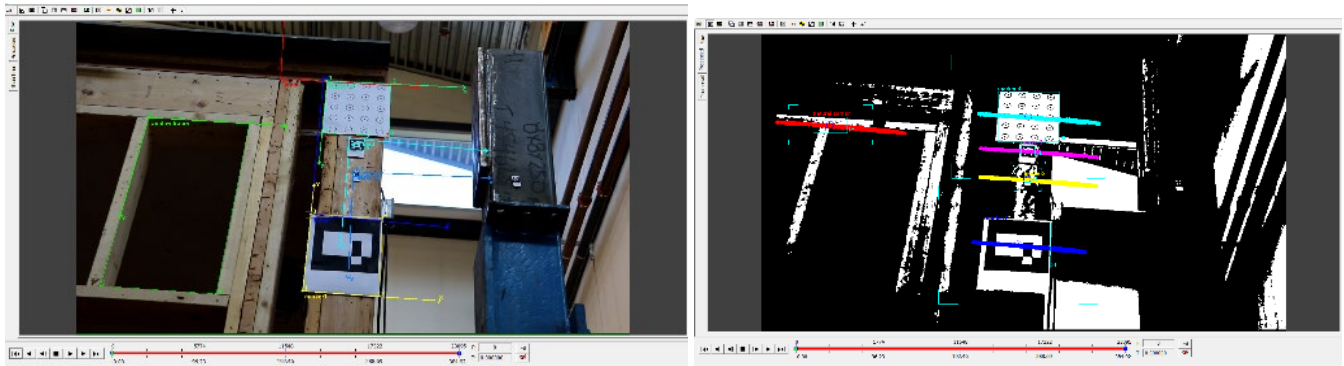


Figure 4 ProAnalyst multi-plane calibration and feature tacking

Once the camera is calibrated, we can use ProAnalyst's image processing tools to remove noise or unwanted features that may interfere with the tracking process. To further improve the data quality, image filtering techniques such as threshold (binary) and morphology, Histogram filtering are also available. The next step is to track the features in the video. ProAnalyst software uses feature matching algorithms to track specific points or targets in the video. The feature tracking algorithm calculates the similarity between the features' descriptors at different frames, and the displacement is then calculated based on the position of the tracked features. Figure 4 displays the selection of five features, including four artificial markers with different dimensions and one natural marker, which is the corner of the window frame. After the feature tracking is complete, the final step is to configure the image. The configuration of the image in ProAnalyst software allows for the display of various parameters, including displacement or velocity of the tracked features, frequency, amplitude, and damping ratio. The displacement per time of each feature is shown in Figure 5, and it is evident that each feature has successfully captured the seismic displacement. Since each feature tracks points according to its defined calibration, the initial different permanent displacement of each marker is shown and should be removed.

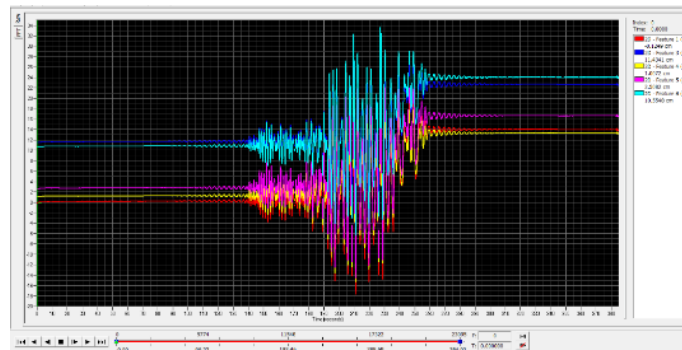


Figure 5 Graph Configuration of X Movement of Tracked Feature

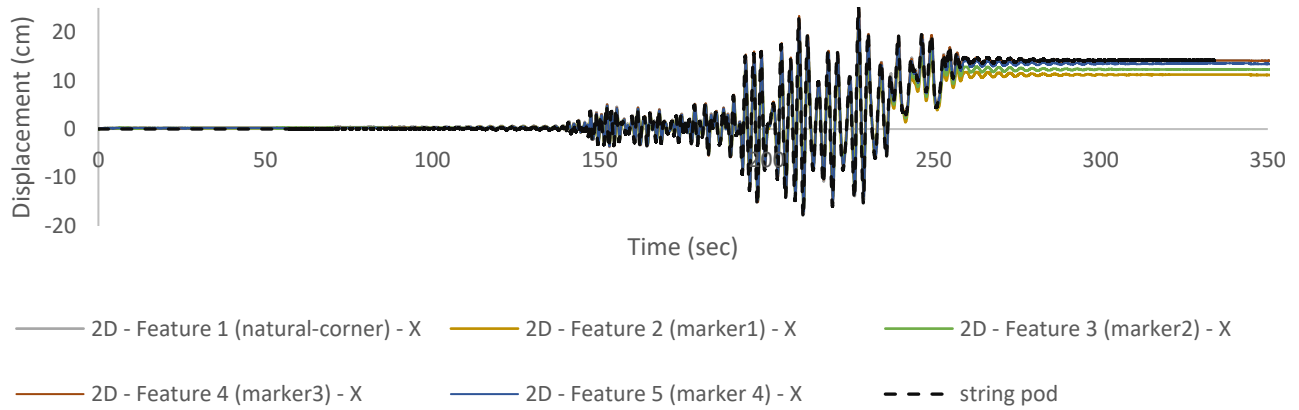


Figure 6 Comparison of Displacement Measurement Techniques: Vision-Based vs. Vibration-Based

In Figure 6, all the natural and artificial markers were effective in capturing the seismic displacement. However, Marker 1 and Marker 2, which were the first and second markers from the bottom, were not able to capture the exact permanent displacement. The author suggests that this could be due to their distance from the top of the structure where the sting pod was installed. Nevertheless, the natural and two other markers were able to capture the displacement accurately.

Moreover, the size of the markers did not seem to affect the results, as long as the quality of the video was good enough and the image filtering was effective in producing clear and visible markers in the binary image.

Overall, the results suggest that both natural and artificial markers can be used effectively for measuring seismic displacement, as long as the placement of the markers is carefully considered. Additionally, the quality of the video and the image filtering techniques used play a critical role in obtaining accurate results.

It is worth noting that the filtering and image processing parts, as well as the quality of the video, play important roles in obtaining accurate results. Since a full HD video was used, even the smallest marker was capable of capturing the seismic displacement. However, in other cameras with different resolutions, it was difficult to obtain accurate results from small markers due to the pixel resolution not being able to accurately capture the correct motion.

CONCLUSIONS

Camera and video-based monitoring methods have emerged as promising tools for measuring the displacement of structures subjected to dynamic loading such as earthquakes or wind events. This study presents an experiment using a fixed camera to track the motion of a full-scale wood-frame school building during an earthquake. The experiment utilizes the feature tracking method of ProAnalyst software to analyze the captured videos and showcase the validity of computer vision in measuring displacement precisely. The results obtained from computer vision were compared to those obtained using traditional displacement measurement techniques such as a string potentiometer. The comparison showed that computer vision's displacement measurements were accurate and demonstrated the potential of computer vision as a valuable tool in the field of structural engineering.

The study found that artificial targets provided the same accurate results as natural targets and that smaller targets could also provide accurate measurements due to image filtering and video quality. The results obtained using computer vision were comparable to those obtained using traditional displacement measurement techniques such as string potentiometers. Future studies will investigate the effects of camera movement, different camera resolutions, and distances on the accuracy of using computer vision for displacement measurements.

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REFERENCES

- [1] Lazebnik, S. (2020). "Computer Vision: Looking Back to Look Forward," <https://slazebni.cs.illinois.edu/spring20/> (accessed Aug. 23, 2022).
- [2] Dong, C. Z., and Catbas, F. N. (2020). "A Review of Computer Vision-Based Structural Health Monitoring at Local And Global Levels," *Struct Health Monit*, 20(2), 692–743, doi: 10.1177/1475921720935585.
- [3] Xu Y., and Brownjohn, J. M. W. (2018). "Review of Machine-Vision Based Methodologies for Displacement Measurement in Civil Structures," *J Civ Struct Health Monit*, 8, 91–110, doi: 10.1007/s13349-017-0261-4.
- [4] Yuanjun, H., Yinfeng, D., Feiyu, G., and Yutong, L. (2021). "Structure Modal Identification Based On Computer Vision Technology," *Vibroengineering PROCEDIA*, 37, 72–77, doi: 10.21595/VP.2021.21945.
- [5] Kromanis R., and Kripakaran, P. (2021). "A Multiple Camera Position Approach for Accurate Displacement Measurement Using Computer Vision," *J Civ Struct Health Monit*, 11(3), 661–678, doi: 10.1007/S13349-021-00473-0.
- [6] Zhang, Z. (2000). "A Flexible New Technique for Camera Calibration," *IEEE Trans Pattern Anal Mach Intell*, 22(11), 1330–1334, doi: 10.1109/34.888718.
- [7] Lee, J. J., and Shinozuka, M. (2006). "A Vision-Based System for Remote Sensing of Bridge Displacement," *NDT & E International*, 39(5), 425–431, doi: 10.1016/J.NDTEINT.2005.12.003.
- [8] Khuc, T., and Catbas, F. N. (2017). "Completely Contactless Structural Health Monitoring of Real-Life Structures Using Cameras and Computer Vision," *Struct Control Health Monit*, 24(1), doi: 10.1002/STC.1852.
- [9] Ngeljaratan, L., and Moustafa, M. A. (2020). "Structural Health Monitoring And Seismic Response Assessment Of Bridge Structures Using Target-Tracking Digital Image Correlation," *Eng Struct*, 213, doi: 10.1016/J.ENGSTRUCT.2020.110551.
- [10] Dong, C. Z., and Catbas, F. N. (2019). "A non-target structural displacement measurement method using advanced feature matching strategy," *Advances in Structural Engineering*, 22(16), 3461–3472, doi: 10.1177/1369433219856171/ASSET/IMAGES/LARGE/10.1177_1369433219856171-FIG2.JPEG.
- [11] Xin, C., Wang, C., Xu, Z., Qin, M., and He, M. (2022). "Marker-Free Vision-Based Method for Vibration Measurements of RC Structure Under Seismic Vibration," *Earthquake Engineering Structural Dynamics*, 51(8), 1773–1793, doi: 10.1002/eqe.3637.
- [12] "ProAnalyst Motion Analysis Software." <https://www.xcitex.com/proanalyst-motion-analysis-software.php> (accessed Apr. 09, 2023).