Vision-Based Displacement Estimation of Large-Scale Infrastructure—A Case Study

CASEY RODGERS, SHUO WANG, BRIAN WELSH, SHAIK ALTHAF V. SHAJIHAN, THOMAS GOLECKI, BRIAN EICK, TRAVIS FILLMORE and BILLIE F. SPENCER

ABSTRACT

Vision-based displacement measurement is promising for infrastructure applications because of its ability to cover traditionally hard-to-access regions, as well as its ability to enable simultaneous dense displacement measurements over large areas within a short time period. This paper proposes, demonstrates, and evaluates a vision-based strategy to estimate the displacement of large civil infrastructure under in-service loading. The first step of the strategy consists of conducting a photographic survey of the structure during a typical loading event. Next, a Kanade-Lucas-Tomasi (KLT) feature tracker is employed on photos to track displacements at various locations on the structure. Finally, computer vision-based techniques including camera motion compensation with 2D geometric transformations, correction for lens distortion, and localized histogram equalization of image intensity are implemented to tackle the inherent challenges with field-collected image data. This paper demonstrates the proposed vision-based strategy on a large, steel miter gate at the lock and dam on the Columbia River at The Dalles, OR. To evaluate the accuracy of the displacement estimation strategy, virtual images of a 3D photorealistic model of the gate with known displacements from a finite element analysis (FEA) model were considered. These displacements were then compared to the FEA displacements projected from the 3D model onto the image plane. The differences between these displacements, which ideally should be zero, directly indicate the error of the proposed strategy. Subsequently, displacements estimated from the field images are compared to those predicted by the FEA. Future work will investigate using these differences to generate high-density data for use in Bayesian model updating. The proposed approach is readily adapted for understanding the deformation of other large-scale civil infrastructure systems under in-service loading and preparing for a FEA model-updating schema.

Casey Rodgers, Shuo Wang, Brian Welsh, Shaik Althaf V. Shajihan, Thomas Golecki, Travis Fillmore, and Billie F. Spencer, Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 205 N Mathews Ave., Urbana, IL, 61802, USA
Brian Eick. Construction Engineering Research Laboratory, Engineer Research and Development Center, US Army Corps of Engineers, Champaign, IL, USA

INTRODUCTION

Periodic condition assessment of large-scale civil infrastructure, such as miter gates, is necessary considering its crucial role in supporting a nation's transportation system and economy. Moreover, civil infrastructure in the US scores a C- according to the American Society of Civil Engineers (2021) [1], adding to the urgency for operators to understand the condition of their assets. Operators intermittently send inspectors to do hands-on inspections, but costs limit the frequency of these visits. Structural health monitoring offers an alternative avenue for periodic condition assessment, using measurements of physical quantities, rather than requiring personnel to gather information about the current condition of the structure manually. However, conventional displacement sensors, such as linear variable differential transformers (LVDTs), require a stationary reference point for installation and direct access to monitoring structures that can be challenging in the field [2]. Additionally, these sensors require reliable power, cabling, and protection against the elements, and can be costly to install, resulting in an intractable implementation on large-scale civil infrastructure.

Computer vision techniques offer promising solutions to civil infrastructure displacement measurement [3] due to their non-contact nature, as well as the ability to cover large areas and achieve dense measurements. With rapid advances in digital photography, computing power, as well as image post-processing algorithms, vision-based displacement measurement strategies have been extensively investigated by many researchers, especially in the past decade. For example, Ye et al. [4] proposed a pattern matching algorithm for multi-point structural displacement measurement and conducted a series of laboratory experiments for performance evaluation. Narazaki et al. [5] evaluated the expected performance of different measurement plans, including camera placement and post-processing algorithms, by simulating the vision-based displacement and strain measurements of miter gates in a photo-realistic environment. The same research group further improved the accuracy of displacement measurement by developing a model-informed approach in a synthetic environment, and then validated the approach's efficacy using laboratory data from a 3D steel truss [6]. However, applying laboratory-developed methodologies to structures in the field is more challenging, due to issues such as lighting changes, moving shadows, wind-induced camera motion, etc., which can negatively impact performance.

In this study, a robust and practical vision-based displacement measurement framework has been developed and is then demonstrated through a case study of an in-service miter gate at a lock and dam on the Columbia River located at The Dalles, Oregon. The displacement estimation was based on applying the classical Kanade-Lucas-Tomasi (KLT) feature tracker [7, 8, 9] to a series of photos of the structure. First, the accuracy of the framework is evaluated using virtual images of a 3D photorealistic model of the gate with known displacements. Subsequently, photographic survey of the in-service gate was conducted during a typical loading event. Various field-related issues, such as wind-induced camera motion, lens distortion, lighting changes etc., were addressed using computer vision techniques. The displacements measured using the proposed vision-based approach were then compared with the FEA displacements, providing necessary information to implement a model updating approach for more detailed representation of the current structure. This vision-based displacement measurement framework can be readily applied to other target structures with only minor adjustments, providing valuable information for infrastructure owners/managers.

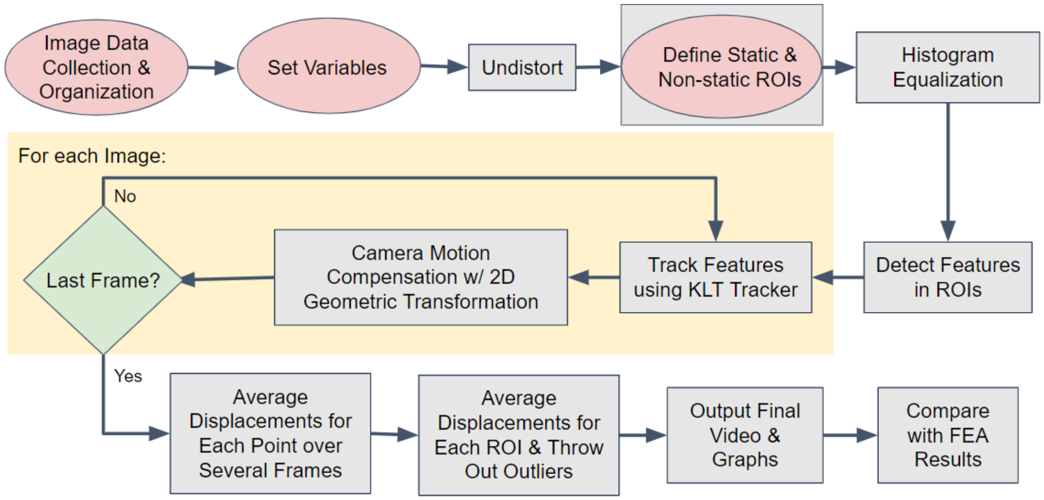

Figure 1. Vision based structural displacement measurement framework.

METHODOLOGY

The vision-based framework for structural displacement measurement developed in this research is summarized in Figure 1. Red ovals indicate user input, gray rectangles indicate actions, and green diamonds represent branches. Red ovals in gray rectangles mean that the user could manually input this information, or it could be automatically extracted from an excel spreadsheet of nodal locations in image coordinates.

First, photographic surveys of The Dalles Lock and Dam were conducted to better understand how the lock's miter gate deforms during operation. Several sets of photos framing various locations on the miter gate were taken during a typical quasi-static loading event. A Nikon Z5 camera was used to capture high-resolution (24.2 megapixels) images every five seconds over the course of a 15-to-20-minute loading event. The camera tripods were weighed down with buckets of rocks and put inside a hunting tent to reduce wind sway effects, and images were taken using the camera's built-in digital timer to minimize physical camera contact during the event.

After the images were captured, pixel displacements of critical points on the miter gate were measured by applying the classical Kanade-Lucas-Tomasi (KLT) feature tracker to the series of photos. To significantly reduce computational cost, only points in regions of interest (ROIs), rather than the entire image, were tracked. Two types of ROIs were considered, termed static ROIs and non-static ROIs. Static ROIs are regions in the image sets that are known to have negligible or incredibly small displacements, such as the concrete monoliths that support the miter gate. These regions are used later to calculate a 2D geometric transformation to correct for camera motion. Non-static ROIs are target regions on the miter gate where displacements are informative of structural behavior. Different variables, including the number of static and non-static ROIs, feature selection method, and number of tracked points in each ROI, can be set to optimize the tracking results for each unique image set.

Several computer vision techniques were applied to the images to track the pixels more easily and more accurately. The images were first corrected for camera lens distortion effect by using the camera lens distortion parameters for our specific cameras. These were obtained by taking photos of a checkerboard pattern at different angles and using the Camera Calibrator App in Matlab. Next, static and non-static ROIs were selected from the undistorted images. These can be chosen by the user or automatically generated from a spreadsheet of node coordinates and the camera's location in the global coordinate system. Then for each ROI, localized histogram equalization was implemented to eliminate shadows and sudden changes in lighting, allowing features to be more distinct and therefore easier to track. Finally, feature points were detected for each ROI using a Harris corner detector. Since the static ROI's are so large, a primarily uniform spectrum of features was chosen over the area. For the smaller non-static ROI's, the strongest features were chosen to get the most accurate tracking results.

After the initial image processing, the feature tracking script iterated over each image in the set and calculated the pixel displacement of the feature points using the Kanade-Lucas-Tomasi (KLT) feature tracker, comparing each image to the first reference image. In computer vision, the Lucas–Kanade (LK) method [7] is a widely used differential method for optical flow estimation developed by Bruce D. Lucas and Takeo Kanade. Optical flow is the apparent motion of brightness patterns in an image, that ideally matches the motion field. The LK method assumes that the optical flow is essentially constant in a local neighborhood of the pixels under consideration and solves the basic optical flow equations for all the pixels in that neighborhood by the least squares' criterion. By combining information from several nearby pixels, the LK method can often resolve the inherent ambiguity of the optical flow equation. It is also less sensitive to image noise than pointwise methods. The Kanade–Lucas–Tomasi (KLT) feature tracker [8] [9] combines feature detectors with the LK method, using an interest point/feature detector such as a Harris Corner Detector [10], to detect good features to track first, and then it does the tracking using the LK method.

Once the KLT feature tracking was complete, a 2D geometric transformation was calculated using the tracked points in static ROIs in the same image to compensate for wind-induced camera vibration. Ideally, the camera should be fixed during the image collection process; therefore, the position of static regions should remain unchanged in the different images. However, due to wind sway, static regions in the image sets are not completely overlapped in different frames. Therefore, the measured displacement of the miter gate is not only actual gate movements but also includes camera motion-induced displacement as well. To remove the camera motion displacement, some typical methods such as Direct Linear Transformation (DLT) and the M-estimator sample consensus (MSAC) algorithm were used [11, 12].

Subsequently, the pixel displacements were stored in an array. To help reduce noise and outliers, a moving average over time was deployed by taking the average of the current frame and the six frames before and after it for each feature point, where the time difference between each frame was 0.5 seconds. Additionally, an average over the feature points within the same ROI was taken to produce one displacement per ROI, where outliers more than one standard deviation away from the mean were thrown out. Also, ROI displacements with a standard deviation more than 0.5 pixels were thrown out to get rid of ROI displacements with bad tracking.

Finally, a FEA model of the gate was created in Abaqus. The displacements at certain times of the fill event were recorded from the FEA in 3D world coordinates. To compare the FEA displacements to the field displacements, both displacements were converted to pixel units in the image coordinate system. Because only a single-lens camera was used to capture images rather than stereo cameras, projecting 2D tracking results into 3D world coordinate system with physically meaningful scale (e.g., meters) is difficult without additional information. Therefore, a feasible strategy is to project the 3D physical displacements from FEA onto the 2D image plane in pixel coordinates. To achieve this 3D to 2D projection, the Camera Calibration Matlab GUI developed in [6] was used to obtain the projection matrix. Correspondence point pairs from the 3D FEA model and the 2D image were selected, and parameters such as focal length, image resolution, and sensor size were used as known constraints. Then, a nonlinear least square regression problem was solved to give the camera location and orientation in the 3D world coordinate system, thus a 3D to 2D projection matrix was further obtained. More details of this camera calibration method can be seen in [6]. For future work, the difference between the FEA displacements and the field displacements will be used for model updating to get an accurate model of the current condition of the structure. A model-updating routine will be implemented by changing the boundary conditions of the Abaqus model at the miter and quoin, calculating the new displacements, and then repeating until the displacements match.

To verify the accuracy of the developed vision-based structural displacement measurement algorithm, a physics-based graphics model (PBGM) of the Dalles miter gate was built in a synthetic environment. A PBGM is a photorealistic, graphical model that is coupled with a physics-based engineering model such as a FEA. For this study, the PBGM was built in Blender using a similar procedure as was developed in [5]. The 3D physical displacement from the FEA was applied to deform the graphical model. Then after setting camera parameters to be the same as the field data cameras and adjusting the location and orientation of the camera according to the camera calibration result, images were rendered from both the undeformed and the deformed PBGM. Figure 2 shows the image rendered from the undeformed PBGM. Then, the developed vision-based structural displacement measurement algorithm was applied to track the pixel displacement between the two rendered images from the undeformed and deformed model, and the tracked displacement was compared with the pixel displacement from the FEA. The difference indicates the accuracy of the developed displacement estimation algorithm.

RESULTS

In this section, results of one of the image sets of a typical loading event are shown as an example. Figure 3 shows the static and non-static ROIs as well as the detected feature points in those ROIs indicated as red crosses. The non-static ROIs were automatically

Figure 2. Undeformed PBGM miter gate

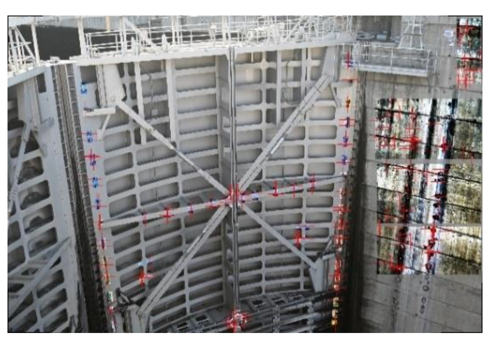

Figure 3. Chosen static and non-static ROI’s.

chosen to match corresponding nodes in the FEA. Points in the four static ROIs were used to calculate the 2D geometric transformation used to compensate for the camera motion-induced pixel displacement. After compensation, the field image pixel displacement for points in the static ROIs are smaller than 0.17 px for the image coordinate x-direction and 0.56 px for the image coordinate y-direction, which is extremely small considering the images are over 6,000 pixels wide and 4,000 pixels tall.

For future model updating purposes and to evaluate the currently proposed algorithm, three cases were compared: Case 1: "FEA", which is the 3D physical displacement calculated from the FEA and then projected onto the 2D image plane. Case 2: "PBGM", which is the 2D tracked displacement between the rendered images from the undeformed model and the model deformed under full hydraulic loading. Case 3: "Field", which is the 2D tracked displacement between the first and the last frame of the image set using the proposed displacement measurement algorithm. All cases show the displacement as the movement of the gate between empty and full hydraulic loading. Figures 4, 5, and 6 show the magnitude of the displacements in pixels at different points on the gate as heat maps for all three cases respectively. The colors are on a sliding scale, so that blue represents the minimum for that set and red represents the maximum, while black represents points that had poor tracking. Heat maps give context for the displacements to better visualize the data. For all three, the displacements near the quoin are the smallest with increasing displacement from the quoin towards the miter, and downwards along the height of the gate. For the field data, there seem to be a few outliers, which could be due to tracking errors from real environmental conditions such as water leaking from the quoin and miter.

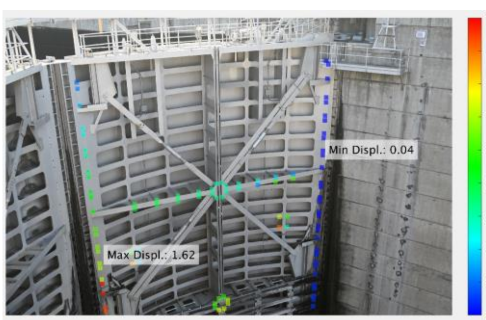

Figure 4. FEA displacement heat map.

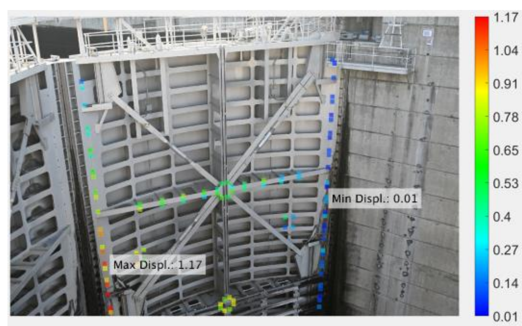

Figure 5. PBGM displacement heat map.

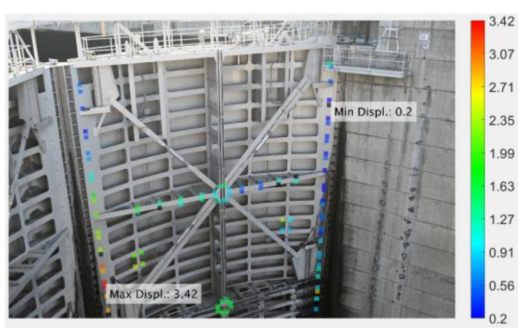

Figure 6. Field displacement heat map.

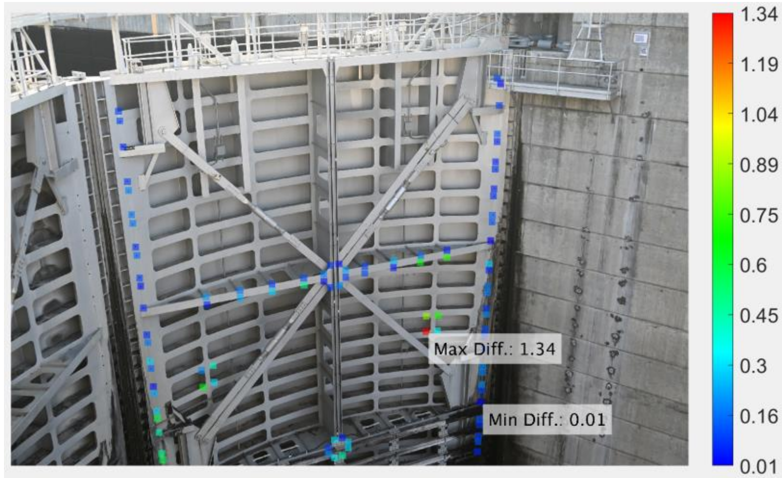

Figure 7. Difference between PBGM and FEA displacement magnitudes.

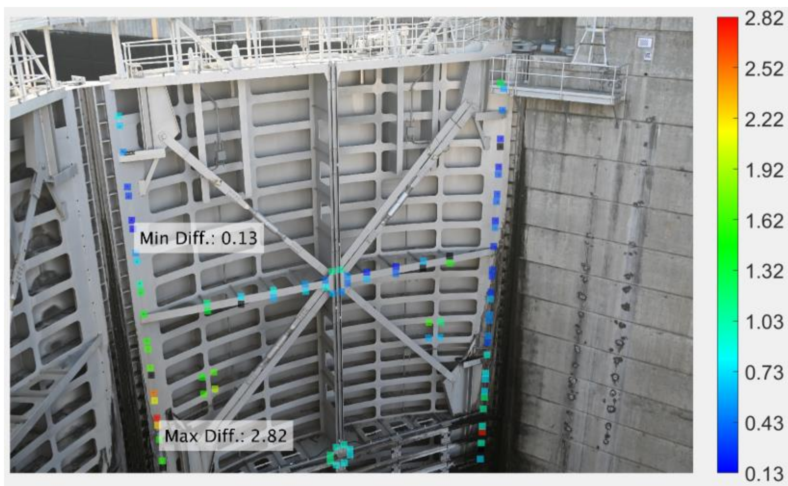

Figure 8. Difference between Field and FEA displacement magnitudes.

However, the differences between cases can be difficult to see in Figures 4, 5, and 6. Figures 7 and 8 show the differences in displacements. The differences between PBGM and FEA seem to be very low with one lone red outlier. This indicates that the displacement measurement strategy has low error and is relatively accurate. The differences between Field and FEA show higher differences downwards along the height of the gate, which could mean those corresponding boundary conditions need to be updated in a model-updating schema.

CONCLUSION

In this paper, a vision-based displacement measurement strategy was developed and applied to a miter gate located at The Dalles, Oregon. A Kanade-Lucas-Tomasi (KLT) feature tracker was used to track displacements at different locations of the miter gate from a series of photos taken during a typical loading event. Computer vision techniques such as camera motion compensation with 2D geometric transformations, camera lens distortion removal, and localized histogram equalization of intensity were implemented to tackle inherent issues with field-collected image data. The accuracy of the developed displacement measurement algorithm was evaluated with the help of a photo-realistic, 3D synthetic model of the gate. For future work, the difference between the FEA displacements and the field displacements will be used for model updating to get an accurate model of the current condition of the structure. A model-updating schema will be implemented by changing the boundary conditions of the Abaqus model at the miter and quoin, calculating the new displacements, and then repeating until the displacements match. With only minor adaptive changes, this strategy can also be readily applied to other large scale target structures, thus attracting interests of owners/managers of infrastructure.

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