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Computer vision-based in-situ bridge displacement measurement

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Abstract

The displacement responses of a bridge structure subjected to moving vehicle load can be used to reflect the information of structural stiffness and load-carrying capacity. This study develops a target-free computer vision-based approach as an alternative to conventional displacement sensors for measuring bridge displacement responses in a contactless manner. This approach involves camera calibration and scale factor determination, natural feature target identification and description, feature matching and tracking. The developed approach is applied for the vibration displacement measurement of Stirling Bridge in Fremantle, Western Australia exposed to normal traffic. The Stirling Bridge has been selected due to the significant number of fully loaded trucks that pass through it, traveling from the North Fremantle Port to Perth City. The identification results agree well with the traffic patterns recorded from a traffic camera installed on the bridge deck. The developed technique provides an affordable and easily deployable alternative to conventional contact-type displacement sensor, which can be used for timely bridge health condition assessment.

1. Introduction

Existing bridge structures exposed to the operational environment for long service life, are prone to performance degradation owing to material deterioration, natural hazards and human-made loading conditions (Peng et al., 2022). Their vertical displacement (deflection) under traffic loads is usually selected as a critical parameter for evaluating bridge performance (Spencer et al., 2020) and establishing a quantitative basis for heavy traffic control. Measuring bridge deflection can be challenging using existing physical sensors; however, the proposed method offers a convenient solution for measuring this deflection. Conventional contact-type displacement sensors, such as the linear variable differential transducer (LVDT), require a stationary reference point, which is often difficult to be found in the field. Furthermore, the measurement range of traditional displacement sensor is relatively short, which limit its application to large-span bridge structures (Hong et al., 2013). To address the limitations of current sensor systems for field applications, the research community has been actively exploring new technologies that can advance the state-of-the-practice in structural health monitoring (SHM). Thanks to the rapid advances in computer vision, the camera-based non-contact vision sensing has emerged as a promising alternative to conventional contact sensors for structural dynamic response measurement and health monitoring. Significant advantages of the vision sensor include its low cost, ease of setup and operation, and flexibility to extract displacements of any points on the structure from a single video measurement.

2. Methodology and technical details

The typical procedure of the vision-based displacement measurement includes:

(1) Video camera setup and calibration. A camera equipped with a lens can be positioned remotely on a tripod for short-term measurements or fixed in place for long-term monitoring. The recorded video can be processed in real-time using image-processing software or stored for post-processing. Prior to use, the camera must be calibrated to establish the geometric relationship between the image coordinates and the corresponding real-world coordinates.

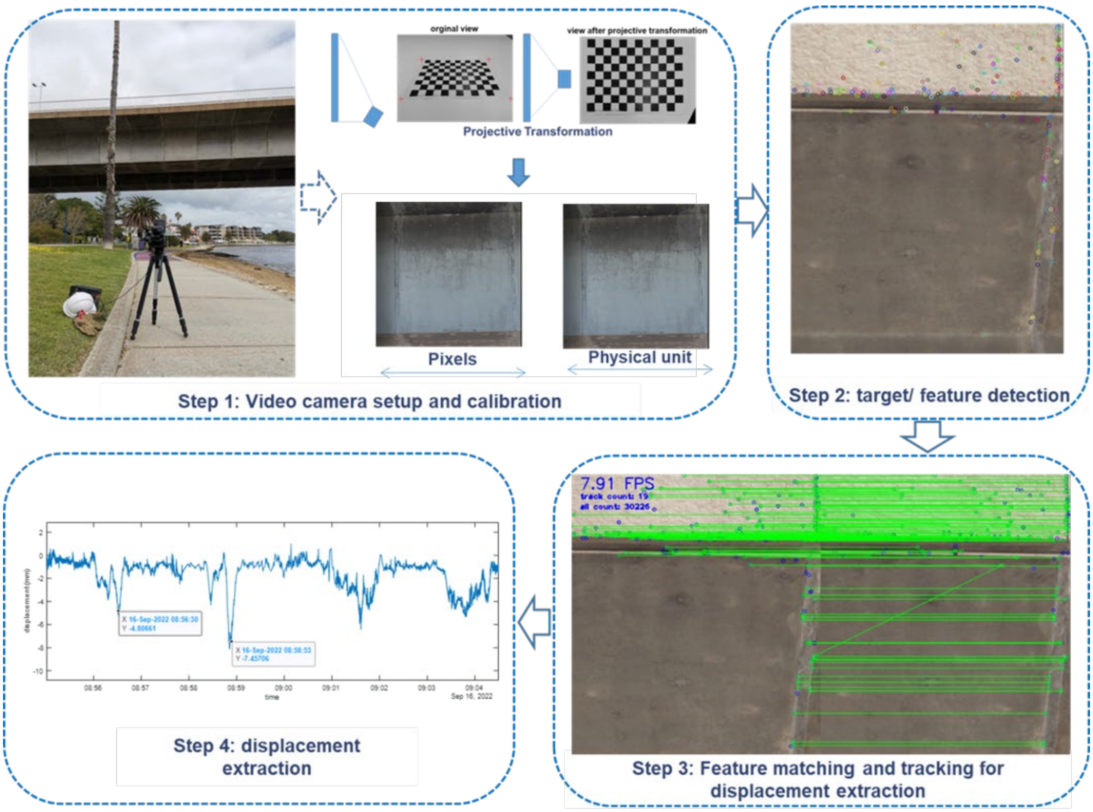
(2) Single or multiple target/ feature detection. Any texture, natural or artificial, on the surface of a structure can be used as a tracking target, provided that it has a distinct pattern that stands out from the surrounding background. However, for accurate pattern matching, a suitable subset with sufficient local texture must be carefully selected for each measurement point.

(3) Feature matching and tracking. To track the motion of a target, its position is identified in a sequence of video images. Advanced vision techniques now offer subpixel tracking accuracy, allowing for precise measurement of even very small movements.

(4) Displacement extraction. The process of extracting displacement involves converting the structural motion, which is initially measured in pixel units, to physical units such as millimeters, using a scale factor.

A technical pipeline of computer vision-based displacement tracking process is illustrated in Figure 1.

Figure 1: Technical pipeline of computer vision-based displacement tracking

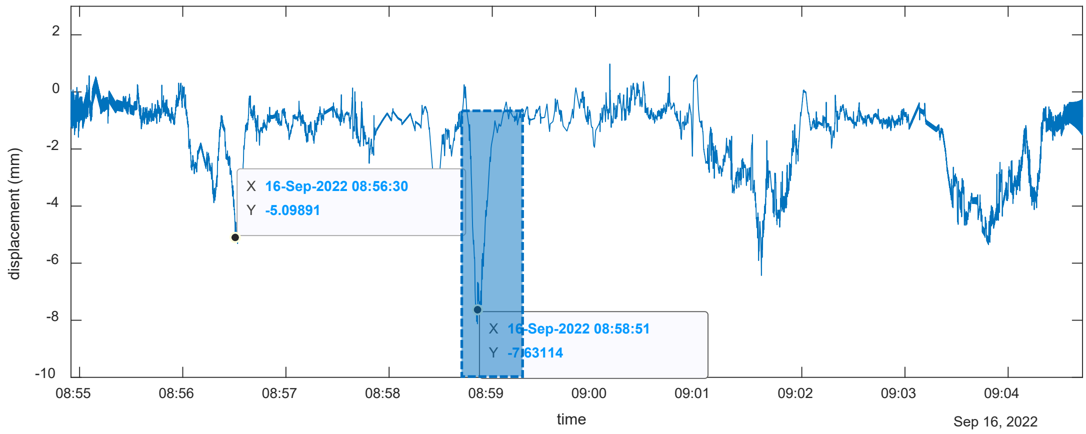


In this paper, four corners of the girder segment side wall are selected. According to the design drawing of the Stirling bridge, the width and height of the girder segment side wall are about 3048 mm and 3305 mm, respectively. The scale factor between the pixel unit and physical engineering unit (mm) is then calculated as 3.3605 mm/pixel. The feature points in the image were detected by the SIFT algorithm and matched by Approximate Nearest Neighbors (FLANN)-based matcher (Bradski and Kaehler, 2008).

3. In-situ validation result analysis

During September 14th -16th, 2022, a series of in-situ bridge tests were carried out. The identification results corresponding to some representative traffic patterns are presented in Figure 2 and Figure 3. Overall, the bridge displacement responses subjected to operation conditions are mainly induced by the traffic load. As evidenced by Figure 2 and Figure 3, the bridge displacement responses reach the valley value at the time instant when the heavy vehicle passes the measurement point (the middle of second span from the south abutment). It is interesting to notice that the shape of displacement curve corresponding to traffic patterns from different directions is different. In particular, when the heavy vehicles are mainly distributed on the Fremantle-Perth city direction traffic lane (as highlighted with the blue box in Figure 2 and Figure 3), the displacement at the left side of the valley value is larger than that of the right side. In contrast, when heavy vehicles are mainly distributed on the Perth city-Fremantle direction traffic lane (as highlighted with the green box in Figure 3), the displacement at the right side of the valley value is larger than that of the left side. The above phenomenon can be explained by the bridge influence line theory.

Figure 2: (a) bridge dynamic displacement between 8:55-9:05 Sep 16, 2022; (b) traffic pattern at 08:56:30 Sep 2022: heavy vehicles distributed on both direction traffic lanes; (c) traffic pattern at 08:58:53 Sep 2022: heavy vehicles mainly distributed on the Fremantle-Perth city direction traffic lane.

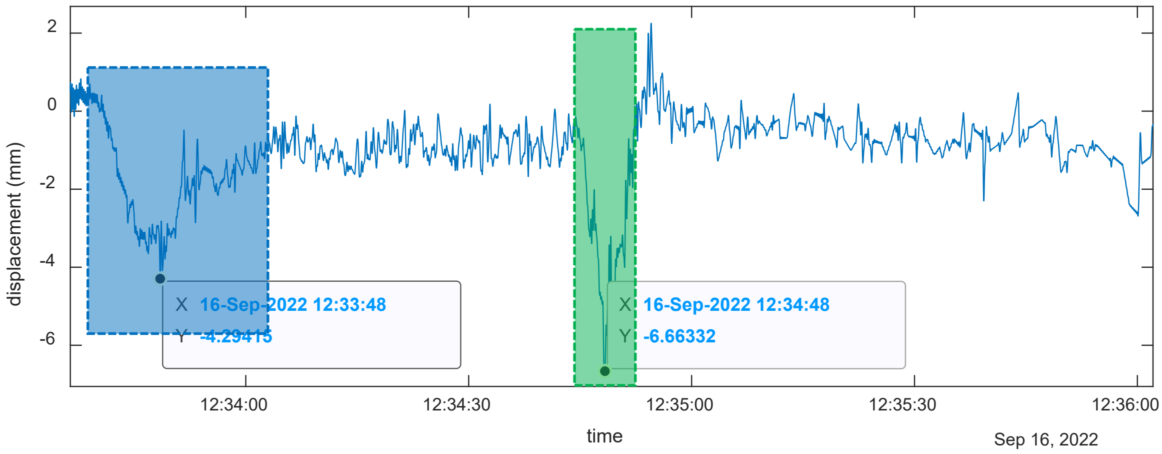


(a)

(b)

(c)

Figure 3: (a) bridge dynamic displacement between 12:33-12:37 Sep 16, 2022; (b) traffic pattern at 12:33:48 Sep 2022: heavy vehicles mainly distributed on the Fremantle-Perth city direction traffic lane; (c) traffic pattern at 12:34:48 Sep 16 2022: heavy vehicles mainly distributed on the Perth city-Fremantle direction traffic lane.



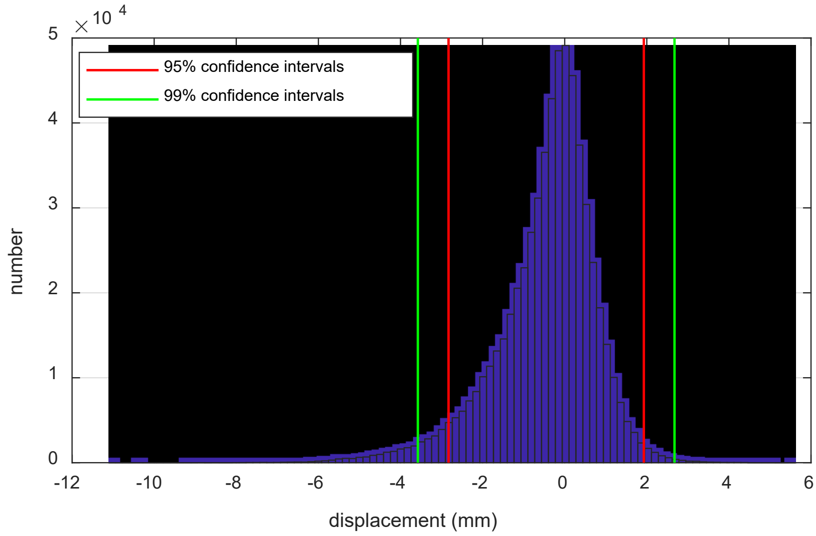
(a)

(b)

(c)

Since the ground truth of bridge displacement responses subjected to traffic load is not available, the authors attempted to indirectly verify the rationality and correctness of the developed target-free computer vision-based displacement tracking algorithm. Figure 4 shows the histogram of bridge displacement responses during the time period of 08:54:47 to 13:54:09 on September 16, 2022, along with their 95% and 99% confidence intervals. The largest displacement response, with a value of 10.39 mm, was identified at 13:16:56. Our analysis reveals that heavy trucks appeared on the bridge deck when the largest displacement responses were observed. It should be noted that the vehicle-induced peak displacement is influenced by various factors such as vehicle weight, speed, type, road roughness, and so on. In the future study, it is suggested to collect additional data to calculate the dynamic amplification factor (DAF) and analyze the effect of vehicle type, vehicle speed on DAF (Ma et al., 2019).

Figure 4: Histogram of bridge displacement response during 08:54:47-13:54:09 Sep 16, 2022.



4. Conclusion and recommendation

Researchers have developed a target-free computer vision-based approach as a substitute for conventional displacement sensors to measure bridge displacement responses in a contactless manner. In-situ validation results revealed that the vision-based displacement subjected to traffic load aligns well with the traffic pattern and is explainable by the bridge displacement influence line theory. However, the accuracy of vision-based displacement identification can be affected by environmental factors such as wind-induced camera motion and light conditions.

To mitigate the effects of wind-induced camera motion and displacement identification errors, the following tasks are recommended: i) use a relatively heavy and solid camera tripod; ii) utilize a case to cover the video camera to avoid wind effects; iii) develop signal processing techniques to eliminate camera motion-induced displacement identification errors. To mitigate the inaccuracy resulted from poor light conditions, it is recommended to adjust the filming angle, shield the camera, and avoid filming during the times of intense direct sunlight.

Acknowledgement

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