The 2020 World Congress on
The 2020 Structures Congress (Structures20)
25-28, August, 2020, GECE, Seoul, Korea

Vision-based Health Monitoring of Critical Joints of a Historical Truss Bridge

*Thanh-Canh Huynh[1)], Jeong-Tae Kim[2)], Quoc-Bao Ta[3)], Nhat-Duc Hoang[4)], and Duc-Duy Ho[5)]

[1),4)] Faculty of Civil Engineering, Duy Tan University, Danang 550000, Vietnam; Institute of Research and Development, Duy Tan University, Danang 550000, Vietnam
[2),3)] Ocean Engineering Department, Pukyong National University, Busan 48513, Korea
[5)] Faculty of Civil Engineering, Ho Chi Minh City University of Technology (HCMUT), VNU-HCM, Ho Chi Minh City 700000, Vietnam
[1)] huynhthanhcanh@duytan.edu.vn

ABSTRACT

Vision-based health monitoring has received significant interests from structural health monitoring and maintenance academia. Despite that, the translation of the vision-based inspection to in-service structures in Viet Nam has been limited so far. Herein, the authors demonstrate the field applicability of a vision-based approach for joints monitoring of a historical truss bridge in Viet Nam. Firstly, a well-established vision-based bolt-loosening monitoring approach is briefly described. Secondly, a field test on the Nam O bridge (Da Nang City) is performed. A digital camera is used to capture the images of representative bolted joints of the bridge. Lastly, the vision-based approach is applied to monitor the bolted joints. The rotations of the bolts in the joints are estimated from the captured images, from which the accuracy of the approach is evaluated. This study is the first case application, demonstrating the field applicability of the vision-based bolt-loosening approach for inspecting a real bridge in Viet Nam.

1. INTRODUCTION

Detecting loosened bolts in critical bolted joints is a well-established topic but very challenging for realistic large connections that often contain hundreds of bolts (Huynh et al., 2018; Nguyen et al., 2017; Nikravesh & Goudarzi, 2017; Wang et al., 2013; Zhang et al., 2017). Visual inspection by human is the simplest method for loosened bolt detection; however, the method is less sensitive to small damage sizes of bolts and also requires professional experiences of the inspector to obtain a certain accuracy. Researchers have

[1), 4)] PhD
[2), 5)] Professor
[3)] Graduate student

developed sensor-based approaches which offer a higher sensitivity to minor damage (Hirao et al., 2001; Huo et al., 2017; Huynh, 2020; Huynh, Ho, et al., 2019; Joshi & Pathare, 1984). However, the sensor-based approaches often need high-performance data acquisition systems in addition to a number of sensors and measurement channels to monitor a large joint. More importantly, the sensor's signals are significantly affected by environmental changes such as humidity and temperature, that often leads to false detections as well as sensor defects.

Recently, the vision-based approach has been studied by many structural health monitoring and maintenance crews and emerged as one of the innovative inspection tools (Cha et al., 2016; Feng & Feng, 2018; Yeum & Dyke, 2015). The vision-based approach offers various unique advantages, such as: non-contact sensing, low cost, simple setup and operation, a capability with monitoring large structures, and immune to environmental changes. The first vision-based method for loosened bolt detection integrates various image processing techniques (Park et al., 2015). This method was then improved with the inclusion of a perspective correction step for enhancing bolt-loosening detectability under arbitrary shooting views (Nguyen et al., 2016). Other researchers developed a vision-based method integrating the Viola-Jones algorithm with support vector machines (Ramana et al., 2018). Zhao et al. trained a deep learning model to track the rotation of the features on the bolt's surface (Zhao et al., 2019). Recently, a quasi-autonomous vision-based bolt-loosening detection method was developed and showed the promising capability of monitoring large-scale bolted connections (Huynh et al., 2019; Lee et al., 2019). The method uses a regional convolutional neural network (RCNN)-based deep learning model for automated detection of numerous bolts in an connection image and robust image processing techniques to estimate the rotation of detected bolts.

So far, researches on vision-based approaches for loosened bolt detection have been not started in Viet Nam. This study is motivated to examine the applicability of the integrated RCNN-image processing method for monitoring large-scale bolted joints of a realistic bridge in Viet Nam. This is because this method is particularly suitable for assessing the structural condition of large-scale bolted joints in realistic structures. To obtain the objective, the following approaches are performed. Firstly, the bolt-loosening monitoring approach based on integrated RCNN-image processing is briefly described. Secondly, field experiments on a historical truss bridge, the Nam O bridge in Da Nang City, is performed. A digital camera is used to capture the images of representative bolted joints of the bridge. Lastly, the vision-based approach is applied to monitor the bolted joints. The rotations of the bolts in the joints are estimated from the captured images, from which the accuracy of the approach is evaluated.

2. VISION-BASED BOLT LOOSENESS DETECTION METHOD

In this investigation, the authors selected a well-established vision-based bolt looseness detection method, which combines the deep learning technology with image processing (Huynh, Park, et al., 2019). In the following, we briefly describe the method; detailed descriptions can be found in the reference (Huynh et al., 2019). Overall, the methodology is accomplished in 3 steps (see Fig. 1). In step 1, images of a bolted connection are captured by a digital camera. In step 2, the captured images are put in a developed deep learning model for automatic bolt detection, and the angles of detected bolts are automatically estimated by several image processing techniques. In step 3, loosened bolts are automatically identified by computing the bolt-rotation angles and comparing them with a defined threshold. The loosening size of loosened bolts is quantitatively estimated.

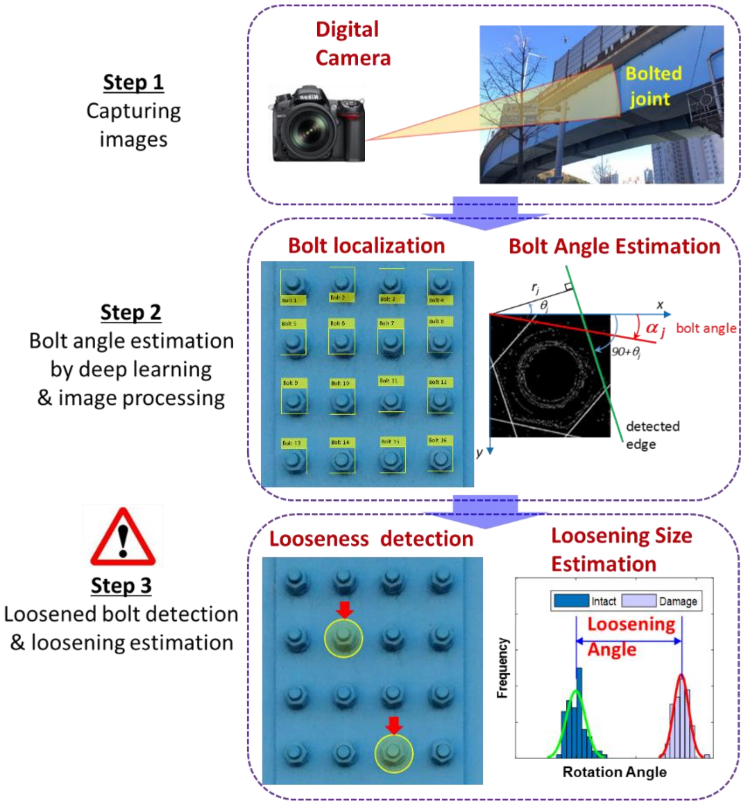


Fig. 1. Vision-based bolt-loosening detection method

2.1. Bolt Detection Approach

The detector has four major steps: (a) to take the input image; (b) to extract object proposals using the selective search algorithm (Girshick et al., 2014); (c) to compute the feature vectors of each extracted object proposal using a CNN model; (d) to classify the extracted object proposals into bolt or not bolt (background).

The selective search algorithm is used to provide regional proposals, which are potentially detecting objects, for the CNN model. The principal of the selective search algorithm can be found in the reference (Uijlings et al., 2013). The CNN model used in this study follows the model in (Huynh, Park, et al., 2019). The network has 15 layers, which are constructed from basic layers: input, convolution, max pooling, fully connected, softmax, output. Each layer is activated by an operator which activates certain features of the detecting object. Those layers are configured to sufficiently extract the feature vectors, which is a dense representation of an object proposal. The RCNN model was trained on a realistic databank and achieved an accuracy of 99.22 % after 5000 iterations (Huynh, Park, et al., 2019).

2.2. Perspective Rectification Approach

Connection images are often captured under a certain level of perspective distortion. Thus, it is necessary to rectify the shooting perspective for an accurate bolt looseness estimation. For that purpose, the homography-based perspective rectification approach is adopted (Nguyen et al., 2016; Yang et al., 2012). The method is based on a projective transformation with the use of homogeneous coordinate systems to transform an image from the image plane into the world plane. Given a homography matrix H, a point in the image plane can be transformed to a point in the world plane. To obtain the matrix H, four points in the reference image and those in the distorted image should be determined. We use the centers of the four corner bolts detected by the bolt detector (Huynh et al., 2019).

2.3. Bolt Looseness Detection Approach

The bolt looseness detection approach for hexagon bolts is described. Hough transform is performed on the image of a detected bolt to detect nut edges and to estimate the bolt angle. The Hough transform algorithm has four main steps: (a) the Canny edge detection is performed on the cropped image to detect the bolt's edges (Canny, 1986); (b) the points of the detected edges are mapped to the Hough space and stored in an accumulator; (c) the true edges of the bolt are extracted from the accumulator by defining a threshold; and finally (d) the extracted edges are sketched on the cropped image and their equations are extracted for bolt angle estimation.

The rotational angle of the bolt ($\Delta\alpha$) is estimated by comparing the present angle with the one obtained in the intact state. For detecting loosened bolts in the connection, the absolute rotational angle is compared with a control limit. The bolt is loosened if the rotational angle is higher than the threshold; otherwise, the bolt is not loosened. A well-established control limit is determined by three standard deviations of the mean with a confidence level of 99.7%.

3. FIELD EXAMINATION ON A HISTORICAL TRUSS BRIDGE IN VIET NAM

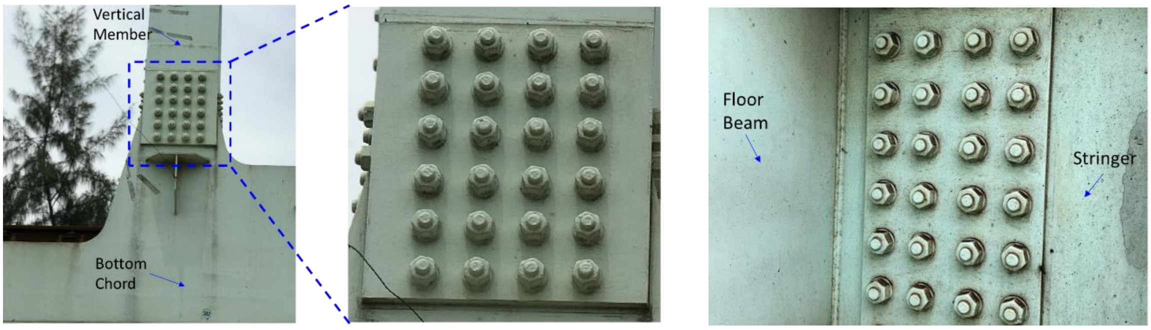
3.1. Experiments on Historical Truss Bridge

The test bridge is a historical truss bridge, the Nam O Bridge in Da Nang City (Viet Nam). The bridge crosses Cu De River and is an important link in the national high way 1A of Viet Nam, as shown in Fig. 2a. The bridge has four spans and each span consists of many large bolted joints, as shown in Fig. 2b. The bridge was constructed before 1975, the year of the reunification of Viet Nam. So far, the bridge has been maintained several times and its current structural performance is an important concern. Health monitoring of the old bolted joints of the bridge is essential to ensure their safety and serviceability.

In this study, the authors used a digital camera to shoot the images of several bolted connections (a resolution of 4032×3024 pixels; AF f/2.8; a focal length of 7 mm). The connection images were input into the vision-based approach for bolt-loosening monitoring. Figure 3 shows the selected images of two bolted joints of the bridge. As shown in Fig. 3a, the first one is the joint between the vertical member and the bottom chord of the bridge (i.e., Joint 1), which has 24 bolts. The second one is the joint between the floor beam and the stringer of the bridge (i.e., Joint 2), which also consist of many bolts, see Fig. 3b.

(a) Location of the Nam O Bridge (b) Real view of the bridge

Fig. 2. Nam O Bridge in Da Nang City, Viet Nam



(a) Joint 1: vertical-bottom chord (b) Joint 2: floor beam-stringer

Fig. 3. Images of two representative bolted joints of Nam O Bridge

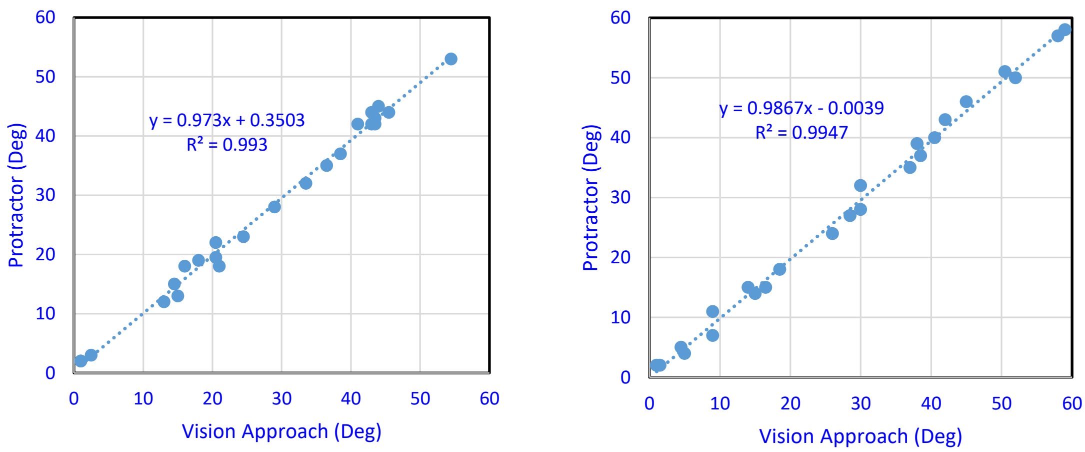
3.2. Vision-based Bolt-Angle Estimation

Joint 1: Vertical Member-Bottom Chord. As the first representative, the results of bolt detection and bolt angle estimation of Joint 1 are presented in Fig. 4a and Fig. 5a, respectively. The perspective distortion of the joint image was well-corrected by the homography algorithm and all 24 bolts of the joint were successfully detected, see Fig. 4a. After bolt detection, the detected bolts were labelled from Bolts 1 to Bolt 24. The labelling rule is based on sorting the bolts' coordinates from left to right and top to bottom. The detected bolts were subsequently cropped in sub-images of single bolts and the angles of the bolts were estimated. Fig. 5a shows a comparison of the estimated angles of the bolts between the vision approach and the manual measurement by a protractor. There exists strong consistency between the two methods (99.3% correlation) in which the estimated bolt angles by the vision approach are well-agreed with the measurement.

Joint 2: Floor Beam-Stringer Joint. As the second representative, the vision-based bolt detection and bolt angle estimation are conducted on Joint 2, as shown in Fig. 4b and Fig. 5b. After the perspective distortion by the homography method, all bolts of the joint were successfully identified by the bolt detector, see Fig. 4b. The detected bolts were then labelled by Bolts 1 - Bolt 24 and the detected bolts were cropped in sub-images of single bolts. Lastly, the bolt angles were estimated by the Hough transform algorithm. Fig. 5b presents a comparison between the vision-based bolt angle estimation and the measurement by the protractor. The bolt angle estimation results between the two methods were well-agreed with a high correlation of 99.5%.

(a) Joint 1 (b) Joint 2

Fig. 4. Perspective correction and bolt detection



(a) Joint 1 (b) Joint 2

Fig. 5. Bolt angle estimation

5. CONCLUDING REMARKS

This study examined the applicability of the RCNN-image processing integrated method for monitoring large-scale bolted joints of a realistic bridge in Viet Nam. Firstly, the vision-based bolt-loosening monitoring approach was briefly described. Secondly, field experiments on a historical truss bridge, the Nam O bridge in Da Nang City, was performed. A digital camera was used to capture the images of representative bolted joints of the bridge. Lastly, the vision-based approach was applied to estimate the bolt angles of the two representative bolted joints (i.e., the vertical-bottom chord joint and the floor beam-stringer joint) in the test bridge. The bolt angles estimated by the vision approach showed a good agreement with the manual measurement by protractor, showing the potentials of the vision-based approach for inspecting realistic bridge connections in the field. So far, there exists limited research on vision-based approaches for loosened bolt detection in Viet Nam. This study is the first evaluation of the vision-based approach on a real bridge in Viet Nam.

ACKNOWLEDGEMENT

This research is funded by Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number 107.01-2019.332

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