



# RESILIENT INFRASTRUCTURE

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## COMPUTER-IMAGE-BASED LOOSENED BOLT DETECTION USING SUPPORT VECTOR MACHINES

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### ABSTRACT

Despite many contact-sensor-based methods have been proposed to monitor and detect structural defects, there are still difficulties compensating for environmental effects and malfunctions of attached sensors, which are main reasons for transmitting false signals. Moreover, regardless of releasing correct or incorrect signals, it eventually leads to human-conducted on-site inspections. In light of these shortcomings, vision-based inspections are considered as potential approach to overcome the explained issues. A number of vision-based methods for detecting damages from images have been developed. However, there are only a few vision-based methods for detecting loosened bolts. Thus, a computer-vision method for detecting loosened bolts is proposed. This study includes two algorithms. The first one is a preprocessing to crop bolt images from bolted-joint images. The second algorithm is a feature extraction by integrating previously proposed algorithms in computer-vision. To accomplish an automated inspection, linear support vector machine is trained and used as a classifier. The robustness of the proposed is verified by the experimental validation; 22 bolt images are used to build a classifier, and 40 bolt images are tested.

Keywords: vision-based; support vector machines; loosened bolt; the Hough transform; damage detection

### 1. INTRODUCTION

A report from the U.S. Federal Highway administration's Nondestructive Evaluation validation Center (NDEVC) (Phares et al. 2001) claimed the concern about the conventional approach to the diagnosis of civil infrastructures. Firstly, the results from human-conducted inspections largely vary due to the intervention of inspectors' subjective opinions. Secondly, such routine inspections are not frequent enough to detect structural damage in a timely manner, and the results are not reliable due to widely varying ratings of a structure's status. Thirdly, many parts of civil structures are not easily accessed by inspectors, making diagnosing them time-consuming.

To tackle the issues, a number of vision-based methods for monitoring and detecting damage of structures have been proposed for civil structures (Cha. 2015 and Chen 2015). Jahanshahi et al. (2011) proposed a method for observing a structure using multi-image stitching and scene reconstruction techniques. Another method for constructing damaged structures in computer-vision was carried by Torok et.al (2013). The authors proposed new crack detection algorithm (CDA) to display damaged spot of a structure after reconstructing 3D model by scanning a damaged structure. These algorithms are attempts on monitoring the global features of structures while many studies focusing on crack are proposed. Huang et al. (2006) developed an image processing algorithm to ascertain cracks on a pavement using matching templates technique. The algorithm automatically converts images into grayscale, and the images are divided into  $8 \times 8$  pixels. The developed algorithm finds the darkest pixels as seed points. After then, it links each seed points, and seed clusters are generated. By the condition of crack features, such as thin, long, and dark, crack-like seed clusters are filtered. Chen et al. (2006) introduced a semiautomatic system for detecting cracks on a concrete surface. To define crack edges, the study applied the first deviation of the Gaussian function. However, this method only works with

manually digitizing points nearby crack on images. The previous study was adopted and modified by Lee et al. (2011). They installed a computational system implementing the former study (Chen et al. 2006) in a vehicle having a boom with cameras. Yu et al. (2007) conducted an inspection with a line digital camera mounted on a robot to detect cracks of a tunnel using Sobel and Laplacian operators. However, it is noted that the robot used in the study supports slow scanning speed, and maintaining a constant distance between the wall and lens is essential. A percolation model based defect-detection (Yamaguchi et al. 2011) of concrete was proposed. By applying termination and skip-added procedures in their previous algorithm (Yamaguchi et al. 2006), efficiency in computing is significantly increased with high accuracy at the same time.

Even though the considerable efforts were made, the above vision-based inspections cannot be recognized as automated approaches without classifiers. Recently, conjugating machine learning in other disciplines has become a natural phenomenon, and many related studies have been proposed in structural health monitoring. Jahanshahi et al. (2013) composed a damage detection algorithm. It considers depth perception to identify cracks on a concrete surface, and machine learning algorithms such as neural network, support vector machines and nearest-neighbour are implemented.

Most engineering structures are subjected to cycling, vibrating, and fluctuating loads. The repetitive load conditions are main mechanisms of bolted-joint failure (Yokoyama et al. 2012). The conventional way to monitor such failure is torque wrench method. However, the quantified result from the method is not reliable (Kim et al. 2009). Although many contact-sensor-based approaches have been proposed and give relatively accurate results, there are many drawbacks. Firstly, contact-sensor-based approaches need a high sampling rate to receive desirable signals from the sensors, which increases the cost of equipment (Wang et al. 2013) and often causes maintenance problems. Secondly, such methods eventually need human-conducted on-site inspections to verify if the alarm is true or false. To overcome these drawbacks, this study proposes a vision based algorithm for detecting loosened bolts from images using image processing technique, feature extracting technique, and linear support vector machine.

## 2. SCHEME FOR DETECTING LOOSENED BOLTS

The proposed algorithm is an automated algorithm to detect loosened bolts from images with four bolts taken by a hand-held smartphone camera having 13 megapixels. Each image was taken in various shooting angles and distances. The general procedure of the algorithm follows the flow chart as shown in Figure 1.

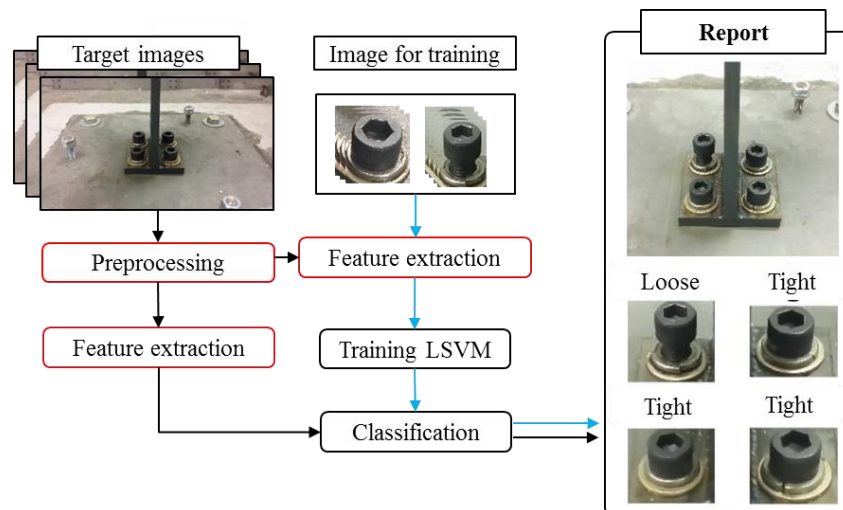


Figure 1: Flow chart of loosened bolt detection

There are two main steps such as training (black arrows) and classifying (blue arrows). In the training step, we manually cropped the prepared images to generate a training set, and manually cropping is the only human-involved task in this approach. The performance of this algorithm is stable unless a training dataset represents the whole dataset.

In the classifying step, the proposed algorithm automatically performs loosened bolt detection following the given flow chart. Firstly, the cropped images go through the proposed feature extraction, and three features for each bolt image are extracted and fed into linear support vector machine (LSVM). On the other hand, the target images, aside from the images manually cropped, are automatically cropped by feeding them into the proposed preprocessing algorithm. Implementing the same feature extraction algorithm used in training step is followed after the preprocessing. Secondly, the images are analyzed and classified by the developed decision boundary from the trained LSVM. Finally, corresponding reports are generated based on the generated results. In the proposed preprocessing and feature extraction, the circular Hough transform (Yuen et al. 1990), the randomized Hough transform (Başca et al. 2005), Canny edge detection (Canny. 1986), and Otsu’s method (Sezgin. 2004) are used. In section 3, the proposed preprocessing and feature extraction algorithms are introduced. In section 4, the experimental validation with 10 images (40 bolts) is conducted.

### 3. IMAGE-PROCESSING

#### 3.1 preprocessing

The objective of the preprocessing is to generate bolt images, and this preprocessing algorithm is developed for the given images resembling Figure 2(a), where four bolts in circular or elliptic shapes on the square plate located in the center of the image. The images from Figure 2(b) to Figure 2(h) represent each preprocessing step. The first step is cropping original images (Figure 2(b)) by the assumption that bolts are in the middle of the image space. This step is for removing unnecessary features and reducing computational cost. The cropped images are denoised and converted into grayscale images as shown in Figure 2(c), where the two techniques are well-known for improving performances in feature extraction. By implementing the circular Hough transform, circles in the image are identified (Figure 2(d)). Based on the locations of clustered circles, tighter images are obtained (Figure 2(e)). The images are simply divided in half (Figure 2 (f)) by the preliminarily known information that the layout of the bolts is symmetric. The divided images are binarized (Figure 2(g)) to minimize errors caused by unnecessary features, such as the column in the image images, and the unnecessary parts are removed by calculating pixel values of the binarized image. The circle detection algorithm is used again, and the circles on bolt heads and washers are localized in the binarized images. Finally, single bolts are collected after splitting the images (Figure 2(h)) based on the localized circles previously.

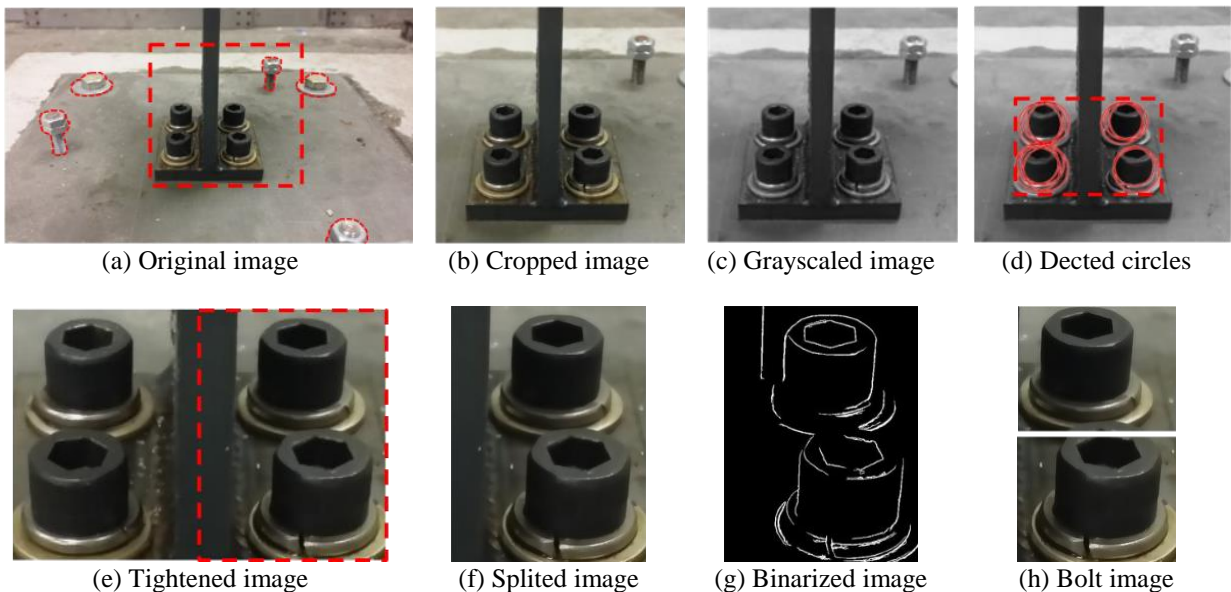


Figure 2: Preprocessing

### 3.2 Feature extraction

In this section, how features are extracted is explained including the reasons for selecting three features instead of a single feature, such as length of exposed thread. After the preprocessing, the algorithm extracts three features, the horizontal length ( $L$ ) of the bolt head, the vertical length ( $H'$ ) of the bolt head, and the vertical length ( $H$ ) between the top of the bolt and the bottom of the exposed thread as shown in Figure 3. There are reasons for selecting three features for this study. If the shooting angles and the distances are the constants, the length  $H$  is enough to differentiate from loosened to tight. However, if loosened and tight bolt images are taken from different distances the images, both images may have the same or very similar values in  $h$ . In this case, a classifier trained with only one feature cannot detect loosened or tight correctly. Differing shooting angles in vertical at the same distance also results in different values of the  $H$ . However, these issues can be readily addressed by setting up the features  $H'$  and  $L$ . In other words, the ratio of  $L$  to  $H$  reflects the distance, and the ratio of  $H'$  to  $H$  reflects the shooting angle.

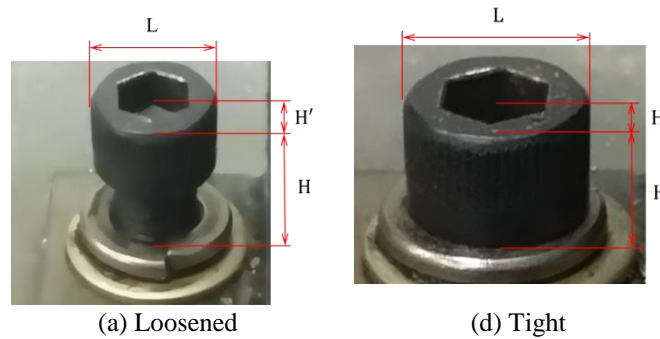


Figure 3: Key features

To obtain the explained features, setting a reference point is necessary, and the centroid of each bolt head from pictured images is chosen as a reference point. One of the collected bolt images generated by the proposed preprocessing is shown in Figure 4(a). Firstly, edges (Figure 4(b)) on images are identified by Canny edge detection, and the randomized Hough transform is applied to find ellipses (Figure 4(c)). The detected ellipse in each bolt head is used as a reference ellipse to crop the surface of the bolt head (Figure 4(d, e)), and each cropped image is converted into a binary image (Figure 4(f)). From the binarized image, centroid (red asterisk) of each image is identified.

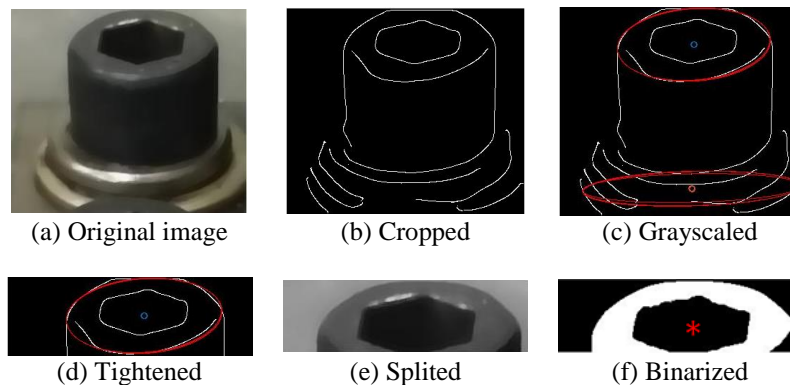


Figure 4: Generate bolt images

The rest is calculating pixel values as shown in Figure 5. In the target image space, the algorithm sets narrow boxes on both sides of image space (Figure 5(a)), and the boxes shrink pixel by pixel. While the boxes are moving, the algorithm integrates the pixel values of the boxes. For example, if the boxes are on the background in Figure 5(a), the values of every pixel in the boxes are ones, and the sum of each box should be over a certain value. With the same idea,  $h$  is also calculated as shown in Figure 5(b) by expanding the narrow boxes from the middle.

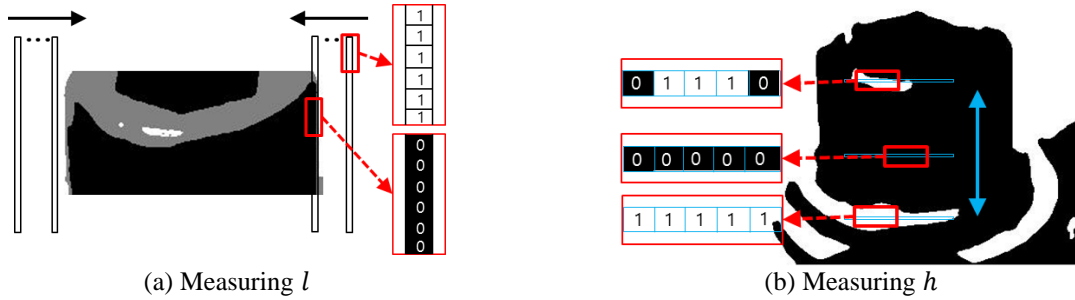
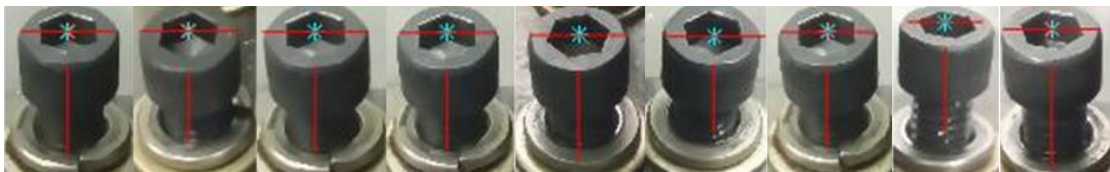


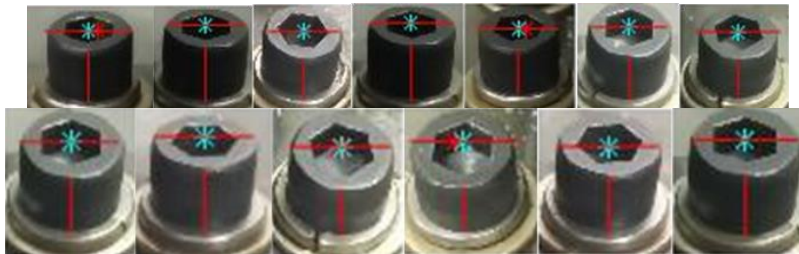
Figure 5: Calculating pixel value

#### 4. TRAINING LINEAR SUPPORT VECTOR MACHINE

As the studied objects have simple and obvious features, linear SVM (LSVM) is exploited to build a robust classifier. To train the LSVM, we used manually cropped images, 9 loosened bolts and 13 tight bolts. By the introduced feature extraction algorithm, all specimens' features are identified regardless of various angles as shown in Figure 6 and its result is also presented in the figure, where asterisk is the centroid of each bolt head, the horizontal red line indicates the width of each bolt head, and the vertical red line represents the vertical length of each bolt from the top to the end of thread. The number of calculated key features is 66, three features (L, H, and H') for each bolt.



(a) Trained loosened bolts



(b) Trained tight bolts

Figure 6. Training set

#### 5. CLASSIFICATION

With the calculated features, the algorithm builds a classifier and the training result is depicted in 3-D parameter space as shown in Figure 7. The gray plane in the figure is called hyperplane separating loose and tight bolts, and cross-dots are support vectors, which are the nearest training data to the hyperplane. With the trained LSVM, the experimental study is conducted with 10 bolted joint images. Some of the representative images are as shown in Figure 8. Each picture has a  $4128 \times 2322$  resolution. The statuses of the bolt connections (loosened or tight) vary in four different conditions. The images were taken in various shooting angles and distances. For the image acquisition, a hand-held smartphone camera supporting 13 megapixels was used. By the introduced preprocessing algorithm, 40 bolt images are generated, and the bolt images are fed into the feature extraction algorithm (Section 3.2), thereby extracting three feature for each bolt image. Based on the boundary condition from the trained LSVM, each bolt image is evaluated, and the algorithm outputs the corresponding reports as shown in Figure 9. The result shows that all the loosened bolts are identified without an exception. All the procedures in this study are conducted in MATLAB with image processing toolbox.

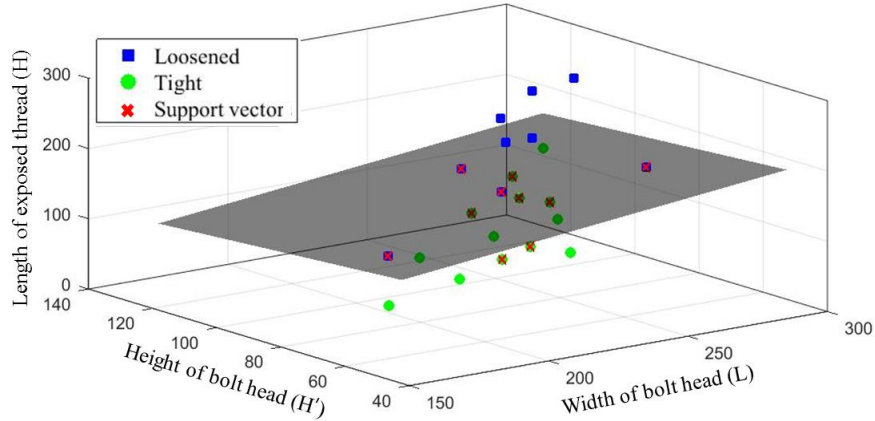


Figure 7. Trained linear support vector machine



Figure 8. Specimens for experimental verification

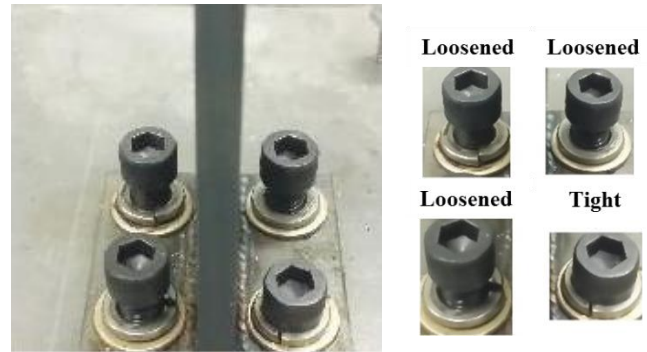


Figure 9. Classification report

This developed method shows robust performances nevertheless the images were taken in various angles and distances, which implies that the scope of the application is broad compared to another previously suggested method that requires a fixed angle and distance. In consideration of the adjustability of the proposed algorithm, it may monitor a larger number of bolts using a single camera and provide accurate information about the states of the bolts. It implies that this non-contact computer-vision method is cost efficient, and it also has many benefits compared to other contact-sensor-based approaches. For example, the general price of a triaxial accelerometer is about \$1,000 (Kurata et al. 2012), which also needs extra equipment to receive data from the sensor. Piezoelectric-based sensors are highlighted as low cost (Mascarenas et al. 2009), but they also need a heavy analyzer. Furthermore, if sensors transmit an abnormal signal, it is unlikely recognizable that the signals are caused by structural damage or sensor damage. On the other hand, the vision-based approach has the advantage that inspectors can observe target structures and check the condition of the camera at the same time. In terms of monitoring cost, the price of the smartphone-level camera is compelling. For example, commercial cameras having the similar level of specifications with the smartphone camera we used is about \$50. Moreover, due to fewer cameras being required, less data storage is needed, which contributes to additional savings in monitoring cost. It is also free from complex environmental effects such as variation in temperature and humidity, compared to the contact-sensor-based approaches, which require complex compensation methods to account for the changes in temperature and humidity. The developed method also requires less computational cost to train the classifier and provides quasi-real-time information of the bolts due to the simplified integrations of the image processing methods. However, this method can detect only fully loosened bolts, and loosened lengths of our dataset were in the range from 3.2mm to 5.8 mm. This method should be improved to detect partially loosened bolts through future studies.

## 6. CONCLUSION

A vision-based method for detecting loosened bolts was proposed. The target objects were bolted joints with four bolts. The pictures were taken by a smartphone camera having a  $4128 \times 2322$  resolution. The image acquisition was supervised by a hand-held camera so that the images had slightly different angles and distances from the objects. As a preliminary step, multiple images were taken, and some of the images were manually cropped to collect bolt images. After the image preparation, the algorithm automatically performed detecting loosened bolts in accordance with the following steps. Firstly, the algorithm extracted features from the manually cropped images and trained linear support vector machine with the extracted features. Secondly, the rest images, aside from the manually cropped images, were fed into the proposed preprocessing algorithm, and bolt images were automatically generated. Thirdly, the same feature extraction algorithm, which was implemented in the previous training step, calculated features from the automatically cropped images. By evaluating the extracted features with the decision boundary from the previously trained LSVM, loosened bolt were detected. To validate the robustness of the proposed algorithm, 40 bolt images were tested, and all loosened bolts were successfully detected without an exception. This proposed non-contact vision-based method showed robust performance for varying vertical angles and distances of the camera. Due to the simplicity of the process, it required less computational cost. In consideration of adjustability of the algorithm, monitoring bolted sections having more bolts is viable. There are some limitations to this method: This algorithm is only effective under predetermined circumstances, such as the layout and the type of bolt. However, the issue can be readily controlled by an automated image recognition technique. Detecting damage from multiple types of bolts can be managed by applying other classifiers, such as non-linear SVMs. As a future research, a modified algorithm, which is widely applicable to general cases, will be developed.

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