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A Computer Vision-Based Method for Bolt Loosening Detection

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Abstract

Routine bolt-loosening inspection plays an essential role in managing and preventing the degradation of our nation's highway bridges over time. Neglecting to perform these inspections could result in public safety concerns. The study of this thesis develops a cost-effective method of bolt-loosening detection based on computer vision. To this end, two input images of the bolted connections are collected at two different inspection times. The feature points are then identified from the input images, based on which a geometric transformation matrix is applied to correct any perspective differences between the two images. Next, we select the image patches of the loosened bolt and apply the geometric transformation again to quantify the angle of the bolt head's rotation. We validated our method through a laboratory test and test results show the success of our method in quantifying the loosened bolt.

1. Introduction

Routine bolt loosening inspection plays an essential role in managing and preventing the degradation of our nation's highway bridges over time. Neglecting to perform these inspections could result in numerous bridges unnoticeably becoming public safety hazards. For example, aged bridges could be easily compromised by extreme flooding, and bridges located in seismic regions could be under significantly increased stress during the event of an earthquake [1]. Furthermore, many bridges are subjected to trucks that are heavier than they were originally designed to accommodate [1]. Ensuring the structural safety of these bridges for the public is the primary motivation for routine bolt-loosening inspection. Addressing any issues identified through bolt loosening inspection prior to the bridge reaching a critical state can significantly reduce the costs needed for repairs. [1].

Bolt loosening detection methods can be classified into three broad categories: sensor-based, percussion-based, and computer vision-based [2]. Sensor-based detection is the most common method used which involves placing sensors on the bolted connections and measuring a certain signal related to bolt loosening (e.g tension load) [3]. This method can be further divided into explicit and implicit detection. Explicit detection, such as with a strain gauge [4] or ultrasonic sensor [5], establishes a direct relationship between the sensor measurements and the tension load. Alternatively, implicit-based detection methods, could apply ultrasonic attenuation and/or excitation analysis [2], typically using a piezoelectric (PZT) ceramic sensor. A PZT sensor relies on the piezoelectric effect to produce an electrical impendence dependent on the stiffness of bolted connections [6]. The data collected from a PZT sensor does not have a clear, explicit mathematical relationship to the tension in the connection and thus may require more extensive interpretation [2].

The second category of bolt loosening detection methods is percussion-based. This method is executed by tapping a steel bolt with an impact tool to produce a sound with specific frequencies correlated to the bolt tension load. Traditionally, this method would require an experienced technician to listen and interpret the frequencies produced [7], recent methods first record the original sound generated following impact. The features can then be extracted to perform analyses and determine the state of the bolt [6], limiting the need for human interaction. This has been accomplished in many different ways such as finding the feature details by utilizing the power spectral density (PSD) of the original audio with a selected frequency segment and using a decision-making tree to determine the degree of looseness [7]. Another method performs an intrinsic entropy analysis and machine learning techniques to determine the state of the bolt [8].

Despite significant advancements in both sensor and percussion-based bolt loosening detections, substantial disadvantages can be found which may limit applications of these methods in practice. First, sensor and percussion-based bolt loosening detection methods require extensive human operations to place sensors on the appropriate bolt or bolted regions which could be time-consuming and labor-intensive. Additionally, many sensors may be highly sensitive to temperature, humidity, and loud noise [6], making results prone to error. Lastly, Kong *et al*. [7] propose integrating robotics to perform percussion-based bolt loosening detection. Although this technique is less labor-intensive, integrating robotics into this method may substantially increase costs.

Computer vision-based bolt loosening detection methods typically use digital images combined with image processing and/or machine learning techniques to determine the status of the bolt. These digital images may be collected through DSLM cameras, smartphone cameras, or unmanned aerial vehicles (UAVs). Computer vision-based bolt loosening methods have made significant advances in the past several years. Huynh *et al.* [9] implemented a trained regional convolutional neural network (RCNN)-based deep learning algorithm which initially detects and crops the individual bolts from the image prior to using the Hough transform to extract the features of the bolt and calculating the bolt angle. Kong *et al*. [10] use feature-based and intensity-based image registration techniques to determine if a bolt had undergone a loosening event. Vision-based bolt loosening detection methods have several advantages over the other previously discussed methods such as being extremely cost-effective and requiring a limited amount of human interaction. Additionally, vison-based methods are more resilient to environmental factors and still yield accurate detection results [2].

The bolt loosening detection method developed in this thesis builds upon a previously established image-based feature tracking approach (Kong and Li [11]) which established preliminary results for bolt loosening detection through feature tracking. However, this study can only offer binary bolt loosening detection results (loosened vs. unloosened), which was limited by its inability to quantify the angle of bolt rotation between images. In this thesis, we provide a novel solution for addressing such a limitation by developing vision-based algorithms that can identify the angle of bolt rotation. The findings of this thesis could serve as a valuable diagnostic tool that provides a measurement of the damage status of the bolt, aiding in a more informed decision-making process regarding structural repairs and/or damage control.

2. Methodology

Figure 1 illustrates our proposed vision-based bolt loosening detection method. Briefly, two input images of the bolted region are taken by a digital camera at two inspection periods. Then, the feature points in the input images are identified through the Shi-Tomasi feature detection algorithm (Section 2.1). These feature points are matched between two input images. To align the two images in the same coordinate system, a geometric matrix estimation is performed as will be described in Section 2.2. Thereafter, image patches of the loosened bolt between inspection periods are manually cropped for estimating the angle of rotation. To this end, the same procedure is applied to the cropped bolt images to detect feature points and estimate another geometric matrix transformation between image patches, based on which the angle of rotation of the bolt is recovered.

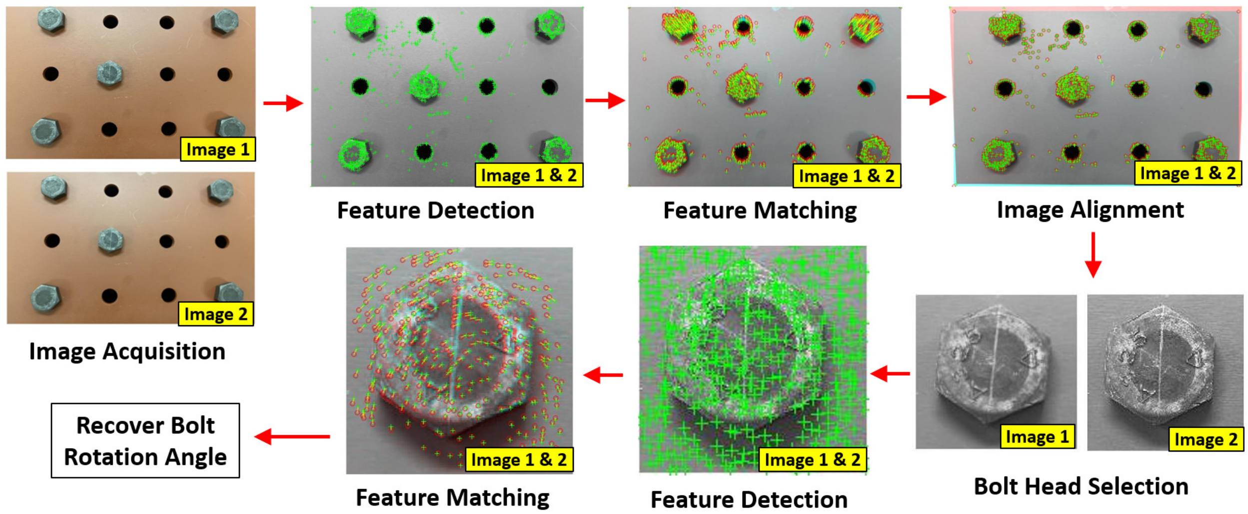


Figure 1. A flowchart depicting each step of the proposed vision-based bolt loosening detection method

2.1 Feature Detection

To align two images with similar perspectives into the same coordinate system, feature points (*i.e.*, interest points) that contain robust image content information must be identified. Ideally, a feature point is distinct from its surroundings, making it identifiable regardless of a change in perspective. There are a variety of techniques that have been used to identify feature points, one of which is corner detection. In both Harris corner detection [12] and Shi-Tomasi corner detection [13], the first step is identifying small windows of the image that may contain corners. If the window contains a corner, it is expected that there will be a large intensity change when the window is slightly shifted in any direction.

Considering the center coordinates of a small window of the original image as (x, y) and a differential displacement in some direction as (u, v), the intensity at each location is $I_{x,y,}$ and $I_{x+u,y+v}$ respectively. A mathematical relationship to quantify this average change in intensity, E, where w is the weights of pixels over the region is shown below.

$$E_{u,v} = \sum_{x,y} w_{u,v} \, [I_{x+u,y+v} - I_{x,y}]^2$$

Given that this expression can be cumbersome and computationally expensive, a first-order Taylor series expansion is used to approximate this intensity change into the expression shown below where g_x and g_y are the intensity derivatives in the *x* and *y* directions respectively [13].

$$E_{u,v} \approx (u, v) M \binom{x}{y}$$

$$M = \sum_{x,y} w(x, y) \begin{bmatrix} g_x^2 & g_x g_y \\ g_x g_y & g_y^2 \end{bmatrix}$$

Once windows with considerably large gradients are detected, corners in these regions are identified by finding the eigenvalues of the matrix *M* and testing these values against a predetermined threshold. Two small eigenvalues correspond to a roughly constant intensity profile within a window while a large and a small eigenvalue correspond to a unidirectional texture pattern. Two large eigenvalues can represent corners, salt-and-pepper textures, or any other pattern that can be tracked reliably [13]. The mathematical formulation of this idea is presented below where λ_1 and λ_2 are the eigenvalues of *M* and λ is the predetermined threshold [13].

$$\min(\lambda_1, \lambda_2) > \lambda$$

Lastly, the eigenvalue threshold must be determined and the corner feature points detected by this algorithm are identified and marked on the image for visual confirmation.

2.2 Geometric Transformation

The computational vision-based bolt loosening detection method implements a geometric transformation estimation for perspective and distortion correction before investigating the state of the bolt. Between inspection periods, the images of the bolted connection may be captured from slightly different perspectives. The images may differ by translation, rotation, scaling, shear, tilt, or typically, a combination of these factors. Given two images taken from slightly different perspectives, specific points such as the edge of a bolt or markings on the bolt head are identified following the method outlined in section 2.1. After the initial feature points are detected, the coordinates of these points are extracted and used to determine the transformation matrix that maps the points from the first image to the second image, which will later be used to correct any perspective distortion.

Since images taken at different perspectives may differ by translation, rotation, etc., the most suitable geometric transformation to estimate is a projective transformation since it has 8 degrees of freedom (DOF). Due to the computational nature of combining multiple transformations, the coordinates of the feature points must first be expressed as homogenous coordinates. If the Cartesian coordinates of a feature point are (x, y), the equivalent point in homogenous coordinates is $(x, y, 1)$, or the same coordinate with the third element of 1. Additionally, converting any 2D homogenous coordinate back into Cartesian coordinates only requires dividing the first two elements by the third. The basic geometric transformations in homogenous coordinates are shown below.

$$\begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \text{Rotation}$$

$$\begin{bmatrix} s & 0 & 0 \\ 0 & s & 0 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \text{Scaling}$$

$$\begin{bmatrix} 1 & 0 & x_0 \\ 0 & 1 & x_1 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \text{Translation}$$

A geometric projective transformation is composed of several simpler transformations. The first is a similarity transformation which is scaling and rotation followed by a translation.

$$A = \begin{bmatrix} s\cos\theta & -s\sin\theta & x_0 \\ s\sin\theta & s\cos\theta & x_1 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \text{Similarity transformation}$$

The second transformation is the shear transformation, *B*, where *k* is the shear element.

$$B = \begin{bmatrix} 1 & k & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \text{Shear transformation}$$

Next, is a diagonal matrix, C, that scales the x and y directions by λ and $\frac{1}{\lambda}$ respectively, essentially preserving the area of planar scaling.

$$C = \begin{bmatrix} \lambda & 0 & 0 \\ 0 & \frac{1}{\lambda} & 0 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \text{Scaling transformation}$$

Finally, an elation transformation, D, essentially scales points directly towards or away from the origin by a scaling factor.

$$D = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ v_1 & v_2 & v \end{bmatrix} \rightarrow \text{Elation transformation}$$

Finally, the projective matrix transformation, H, can be expressed as a combination of these simpler transformations shown below.

$$H = ABCD = \begin{bmatrix} s\cos\theta & -s\sin\theta & x_0 \\ s\sin\theta & s\cos\theta & x_1 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & k & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \lambda & 0 & 0 \\ 0 & \frac{1}{\lambda} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ v_1 & v_2 & v \end{bmatrix}$$

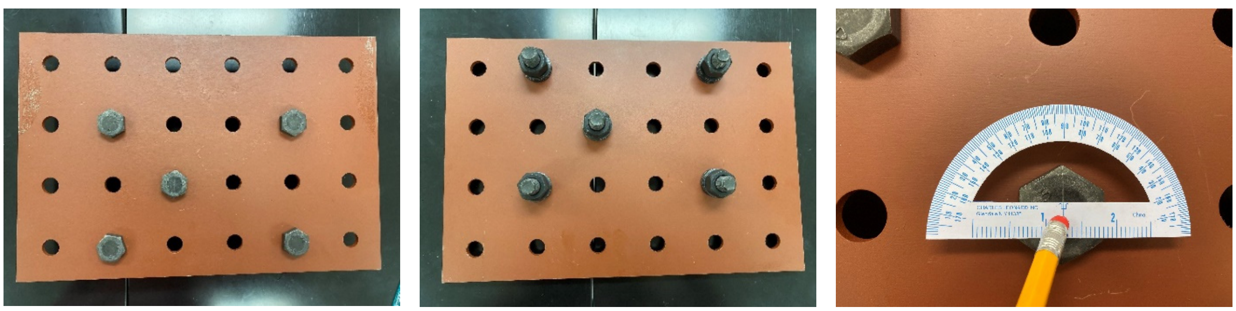
This can be further condensed and generalized into the transformation matrix shown below where the input column vector is the coordinates of the feature points in the original image and the output column vector is the coordinates of the feature points in the second image.

$$
\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}
$$

Given the appropriate coordinates (*i.e.*, four or more feature points) [14], the geometric projective transformation can be estimated along with the inverse to align the two images in the same coordinate system and proceed with further bolt loosening analyses.

3. Results and Discussions

3.1 Experimental Setup



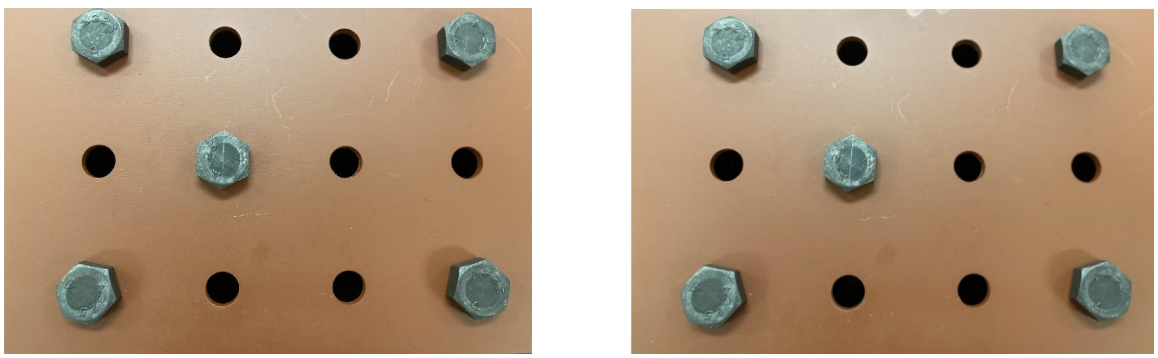
(a) (b) (c)

Figure 2. (a) The front side of the steel plate; (b) the back side of the steel plate; and (c) the application of a protractor to manually measure the angle of rotation. The bolts, washers, and nuts are shown in (a) and (b).

The experimental setup consists of a 12 *in* by 18 *in* by 0.25 *in* steel plate shown below in Figure 2 with 2.25 *in* long, grade A325 steel bolts, 0.75 *in* diameter washers, and 0.75 *in* diameter nuts. The images were captured with an iPhone 11 camera with the F-stop value set to 6.3. The images have a resolution of 840 pixels by 1320 pixels and were captured from approximately 1.5 *ft* away from the steel plate. To validate the results of this method, the actual angle of rotation of the loosened bolt was manually measured using the protractor shown in Figure 2c and compared to the results obtained from the vision-based method.

3.2 Test Results and Discussions

The two input images used to validate our proposed method consists of one image of the steel plate at initial status (Figure 3a) and the second image where a bolt was manually rotated 3° clockwise shown in the second row and second column in Figure 3b. The two input images were taken under a room ceiling lighting condition and the camera was held directly above the plate to prevent harsh shadows or glaring with the flash turned off. The bolt located in the center of the plate (*i.e.*, located in the second row and the second column in Figure 3b) was slightly rotated between the two photos while the remaining four bolts were left untouched.



(a) (b)

Figure 3. Two input images to validate our proposed bolt loosening detection method. The bolt on the second column and row is manually loosened counterclockwise.

Our image processing workflow starts with Shi-Tomasi feature detection which is shown in Figure 4a. Thereafter, the feature points matched between the two images are shown in Figure 4b. where the red circles are the feature points from the first input image and the green crosses are the same feature points identified in the second input image. The matched feature points are then used to estimate the geometric transformation matrix, which is applied to the second input image to align two input images into the same coordinate system shown in Figure 4c. Magnified images of the loosened bolt at each step in Figure 4 are shown in Figure 5. Figure 5c shows the rotational movement of the bolt where the feature points did not follow the same movement pattern and were therefore excluded from the alignment process.

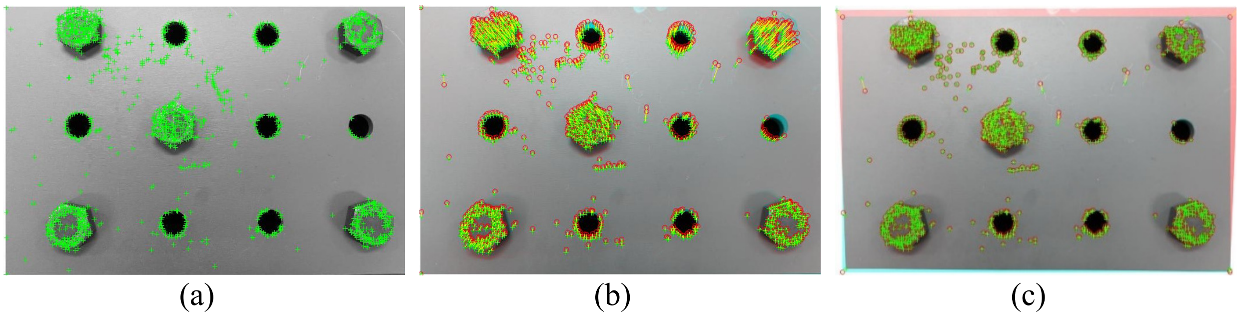


Figure 4. The feature points detected (left), the matched feature points between the two images (middle), and the images aligned in the same coordinate system (right)

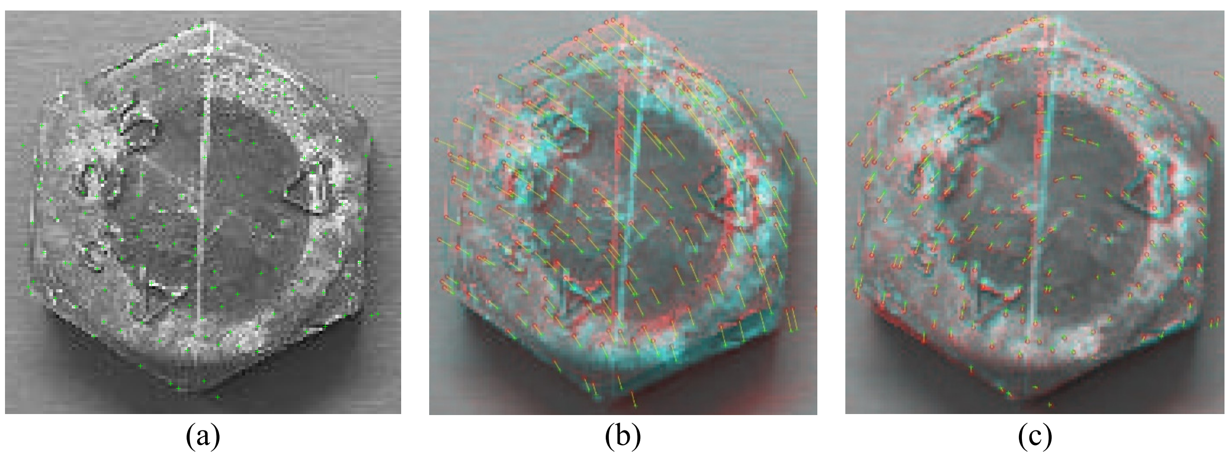
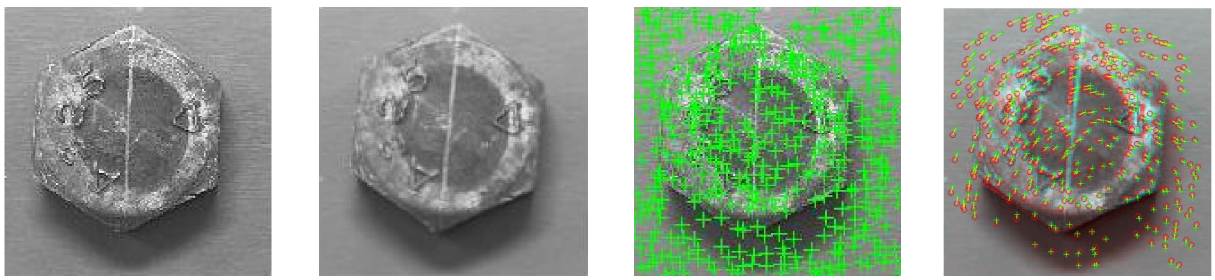


Figure 5. (a) Magnified view from Figure 4a; (b) magnified view from Figure 4b; and (c) magnified view from Figure 4c. Magnified views are taken from the region of the loosened bolt.

By observing the rotational movement of the feature points on the loosened bolt after alignment (Figure 5c), the loosened bolt was manually identified from the image to further quantify the angle of rotation. To this end, the image patch containing only the bolt was selected and cropped from two input images shown in Figures 6a and 6b. Next, the feature points on the bolt head are detected shown in Figure 6c. Finally, those feature points are matched between the two images shown in Figure 6d. Since the two input images now lie in the same coordinate system as a result of the alignment process previously discussed, the geometric transformation estimated from the feature point movement indicates the bolt head rotation. Finally, the rotational angle of the bolt head is recovered from the geometric transformation matrix.



(a) (b) (c) (d)

Figure 6. (a) and (b) are cropped image patches from the bolt head from two input images after image alignment; (c) shows the detected feature points in the first input image; (d) shows matched feature points between two input images after image alignment.

The results from the MATLAB code returned the recovered angle for the previously described dataset as 3.0188°. The angle of rotation measured with the protractor shown in Figure 7 was recorded as 3°. The percent error between these two values is 0.627%. This indicates that the method described could provide accurate results for quantifying the angle of bolt rotation where the perspective difference between input images is relatively small and where the bolt does not rotate significantly between inspection periods. More testing is needed to confirm the accuracy of this method for larger rotation angles and circumstances where the perspective shift between input images is more drastic.

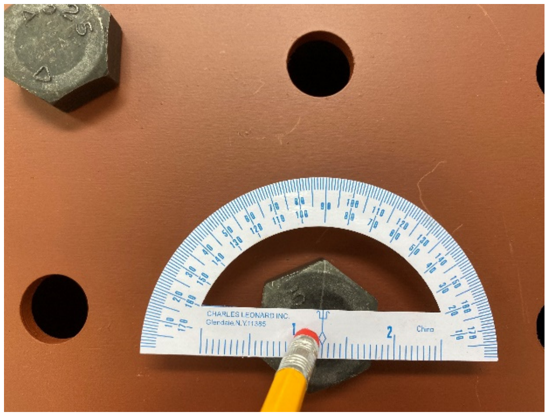


Figure 7. The manually measured bolt rotation angle using a protractor

4. Conclusions

Routine bolt-loosening inspection plays an essential role in managing and preventing the degradation of our nation's highway bridges over time. The purpose of this thesis was to develop a novel bolt loosening detection method that is capable of quantifying the angle of bolt rotation. A laboratory test was conducted to validate our method using a steel connection plate. Our proposed method was able to detect the angle of rotation with a 0.627% error from the manually measured rotation angle. This proposed method provides the ability to both identify loosened bolts and quantify the angle of rotation. The findings of this thesis could serve as a valuable diagnostic tool that provides measurements of the damage status of the bolt, aiding in an informed decision-making process regarding repairs and/or damage control. Further work will focus on investigations of the viability of our method against varied lighting and perspective changes between input images.

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