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Research of Highway Bridge Settlement Monitoring Technology based on Machine Vision

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Abstract: ***In view of the significant impact of deep foundation pit excavation on the surface of surrounding roads and bridges, the widely used monitoring technology still relies on manual detection means, which leads to the consumption of a large number of human and material resources, and the efficiency is relatively low. Therefore, this paper provides a method and system of highway bridge pile foundation displacement monitoring based on machine vision. Through real-time automatic monitoring of highway bridge pile foundation settlement changes, it provides targeted suggestions and guidance for highway bridge maintenance during foundation pit excavation. At the same time, a new type of marker module is provided to enhance the accuracy of feature point recognition in image processing. The results show that the highway bridge settlement monitoring system based on machine vision method can automatically monitor the highway bridge pile foundation settlement in real time with high accuracy, and improve the safety and stability of highway bridges during construction.***

Keywords: Highway bridge, Machine vision, Settlement monitoring, Target recognition**.**

1. Introduction

In recent years, the world population has been continuously increasing, leading to greater pressure on urban transportation. As a result, subways have gradually become an important mode of travel. The construction of subway stations first faces the challenge of foundation pit excavation. Due to limitations such as terrain and funding, foundation pits sometimes need to be adjacent to highway bridges. When excavating foundation pits near highway bridges, it can cause changes in the surface around the bridges, altering the boundary conditions of the bridges, thus affecting them [1]. Therefore, during the construction of foundation pits, one of the key focuses is to ensure the normal operation of nearby road traffic and the stability of highway bridges by conducting high-precision monitoring of the settlement and displacement deformation of the highway bridge pile foundations around deep foundation pits.

The existing methods for monitoring bridge settlement and deformation include traditional monitoring methods, the laser Doppler vibrometer method, and the global positioning system (GPS) method [2]. Traditional monitoring methods are mostly contact-based and require monitoring personnel to operate instruments such as micrometers for measurements [3]. Although this method has relatively high accuracy, it is inefficient and has a low degree of automation. The laser Doppler vibrometer method offers high accuracy and can monitor local vibrations, but it has high cost requirements and the precision is significantly affected by the laser emission angle. The GPS method has a high degree of automation and strong applicability, but its measurement accuracy is relatively low and it requires specialized knowledge.

With the continuous improvement of visual processing technology, vision-based measurement methods have gradually emerged. Due to their low cost and easy installation, these methods are widely used in fields such as bridges, pipelines, and autonomous driving. For example, drones can identify bridge structural cracks [4], pipeline defect monitoring [5], and intelligently avoid obstacles [6]. For highway bridge pile foundations, visual monitoring uses cameras to capture images of marked modules fixed on the pile foundations. By recognizing feature points, the pixel coordinate changes of these points over adjacent time intervals are calculated and then converted into actual displacements, thus obtaining the settlement displacement of the highway bridge pile foundations.

The article presents a machine vision-based method for monitoring the settlement and displacement of highway bridge pile foundations. This method can achieve multi-threaded data aggregation, long-distance real-time monitoring, and operates effectively both day and night. It uses multiple cameras to capture high-frequency images of bridge pile foundation markers at different locations. These data sets are processed simultaneously using multi-threading, combining the settlement data of each bridge pile foundation and the overall linear deformation of the bridge.

2. Bridge Settlement and Displacement Monitoring Method

2.1 Principle of Vision-based Bridge Settlement and Displacement Monitoring

The sampling cameras are arranged in a parallel multi-camera configuration, with each bridge pile foundation corresponding to a camera that is equipped with a measurement marker module. The camera lens captures images of the targets, and the program identifies the image information of the marker modules to obtain the displacement changes in the pixel coordinate system of the feature points. Based on the displacement changes of the feature points and using coordinate transformation formulas, the deformation data of each observation point are obtained, allowing for the determination of whether the bridge pile foundation has settled and if the overall linear deformation of the bridge has occurred.

2.2 Marker Module

The main principle of the machine vision-based displacement monitoring method for highway bridge pile foundations is to extract the relevant displacement of feature points based on the features of the marker modules collected by the camera. Therefore, selecting appropriate marker modules is one of the key factors for the success of the monitoring method.

The marker module combines markers with a light source. In this article, the structure of the marker is as shown in Figure 1. The marker uses a four-circle rectangular distribution method, where four equal-sized circles are arranged in a rectangular pattern, with each circle's center located at the vertices of the rectangle. The edges of the circles are gradient-processed. The light source uses a backlight panel, placed behind the marker to ensure that the monitoring equipment can operate both day and night.

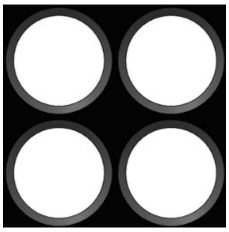

Figure 1: Marker

2.3 Lighting and vibration

The lighting conditions are one of the critical factors affecting the success of image recognition, significantly influencing information transmission and image quality. They also affect the recognition of features in the image. Therefore, to achieve better image quality and enhance the robustness of image recognition methods, it is necessary to evaluate the lighting conditions.

By using a backlight panel as a light source to enhance the contrast between the central circle of the marker and its surrounding area, and by comparing the grayscale values of the Region of Interest (ROI) in the captured images with a set threshold, adjustments to the camera exposure parameters are automatically controlled by the program when the grayscale values are too high or too low. This approach ensures stable image acquisition even in bright light environments, thereby guaranteeing stable subsequent image recognition processes.

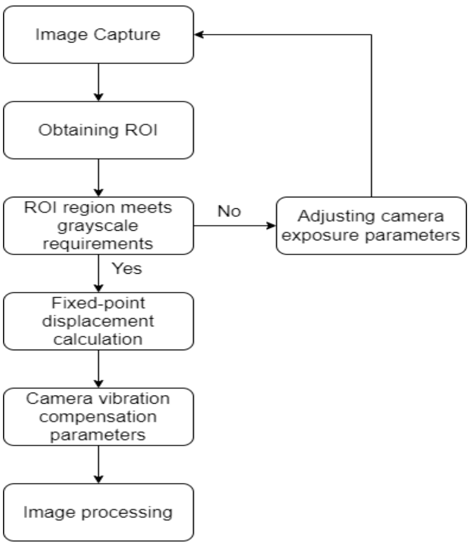

Figure 2: Light and vibration compensation

Camera vibration significantly affects the accuracy of displacement monitoring. Camera vibration introduces additional errors to displacement monitoring, making effective reduction of camera vibration a crucial prerequisite for accurate displacement monitoring.

To mitigate the impact of camera errors on displacement monitoring, image correction and compensation are performed on the acquired images. Firstly, a fixed point within the camera's capture range is selected as an absolute reference point. This point remains stationary and is unaffected by camera vibration or bridge settlement changes. By calculating the pixel coordinates of this point, an offset is determined to derive compensation parameters. Ultimately, these parameters are used to compensate for vibrations during bridge displacement calculations.

2.4 Image Recognition Methods

Machine vision-based image recognition methods include ROI extraction, target identification and coordinate calculation, and coordinate transformation.

Template matching involves searching for and comparing a template image within a target image to find the most similar region based on correlation calculation. The article utilizes the normalized cross-correlation method for template matching, as shown in equation (1), where a result of 1 indicates the best match.

$$R(x,y) = \frac{\sum_{x',y'}(T'(x',y')\cdot I'(x+x',y+y'))}{\sqrt{\sum_{x',y'} T'(x',y')^2 \cdot \sum_{x',y'} I'(x+x',y+y')^2}} \tag{1}$$

In the equation, $T'(x',y')$represents the pixel values of the sliding window on the image to be analyzed. represents the pixel values at the corresponding position in the image being analyzed. x',y' denote the offset of the sliding window, while x and y denote the position coordinates of the template image.

Once the position of the target image in the image is determined, the size of the ROI (Region of Interest) is determined based on the size of the feature area.

For the obtained ROI image area, after threshold binarization and morphological transformation, the Hough gradient algorithm is used to obtain the coordinates of all circles' centers in the image. Then, by setting the area of the target circle, the target circles are selected. The centers of the four target circles are used as vertices to construct a rectangle. The centroid method is used to calculate the center coordinates of the rectangle, with the formula:

$$(x_0, y_0) = \left(\frac{\sum f(x_i,y_i)x_i}{\sum f(x_i,y_i)}, \frac{\sum f(x_i,y_i)y_i}{\sum f(x_i,y_i)}\right) \tag{2}$$

In the formula, represent the pixel coordinates of the centroid point, and represent the horizontal and vertical coordinates of the i-th pixel point.

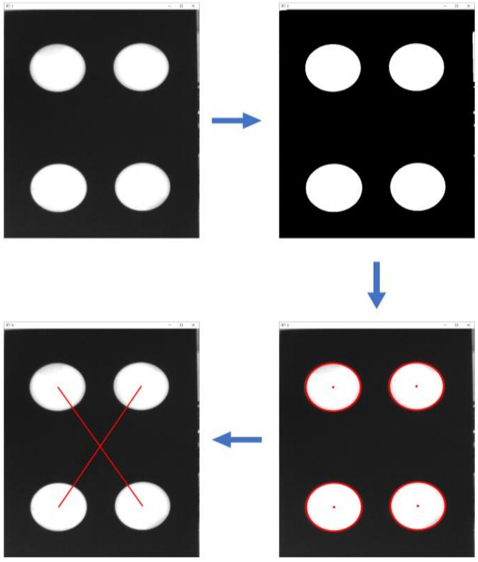

Figure 3: Feature recognition

To convert the pixel coordinates of the image to actual coordinates, it is necessary to determine the scaling factor. The system uses equation (3) to compare the actual size of the marker module with its pixel size, thereby obtaining the actual scaling coefficient.

$$k = D_r / D_p \tag{3}$$

In the formula, D_r、 D_p represent the actual size and pixel size of the marker.

3. Experimental Analysis

3.1 Accuracy Experiment

The experimental equipment includes a lens with a 25mm focal length, with the marker module fixed on the working plane of a stepper motor. The image acquisition device is fixed in place, maintaining a 50cm distance between the camera lens and the marker module, with the lens's optical axis perpendicular to the marker module. A displacement sensor is used for comparative measurement. Machine vision image processing technology is used to obtain the pixel coordinates and actual coordinates of the target image's center point. The displacement sensor monitoring program is used to compare the accuracy and stability of the displacement monitoring.

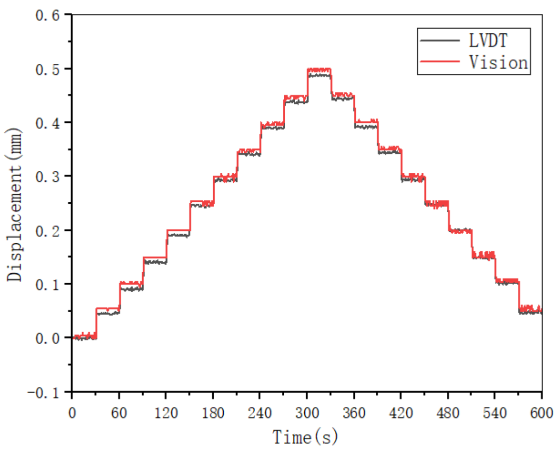

Figure 4: Displacement trend chart

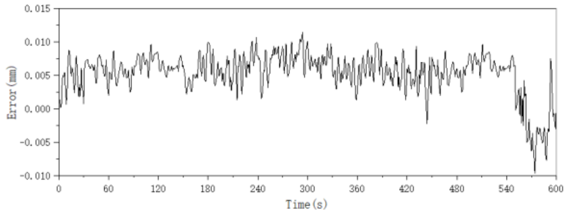

Figure 5: Error variation diagram

From Figures 4 and 5, it can be observed that during the stable period, the data from the machine vision-based monitoring method and the LVDT measurements show noticeable fluctuations after each displacement, but the cumulative changes remain largely unchanged. As the displacement amplitude increases, the error between the two sets of values decreases, with the error fluctuating within 0.015mm. During the displacement loading and unloading process, the maximum displacement error remains at 0.012mm, indicating that the resolution of the monitoring system based on this method can reach 0.05mm.

In the experiments, the maximum relative error often occurred during periods of relatively small displacement. Although the error value was not particularly large, the relative error appeared more significant due to the small displacement load. When the displacement load was larger, the relative displacement error remained within 5%, demonstrating that the system based on this method has high accuracy.

3.2 Field Experiment Verification

The field experiment was conducted at the construction site of the Balityai Station in Phase I of Tianjin Metro Line 7. The marker module was fixed to the side of the bridge pile foundation using bolts, with the camera's optical axis perpendicular to the plane of the marker module. The maximum distance between the camera and the marker module was 44 meters. The arrangement of the camera and marker module is shown in Figure 6. The camera was rigidly connected to the camera bracket, and the camera bracket was rigidly connected to the ground. At the same position where the marker module was installed, a laser displacement sensor (LDS) was used for monitoring. The LDS had a minimum resolution of 0.002mm and an accuracy of 0.012mm, and it monitored vertical displacement for the control experiment.

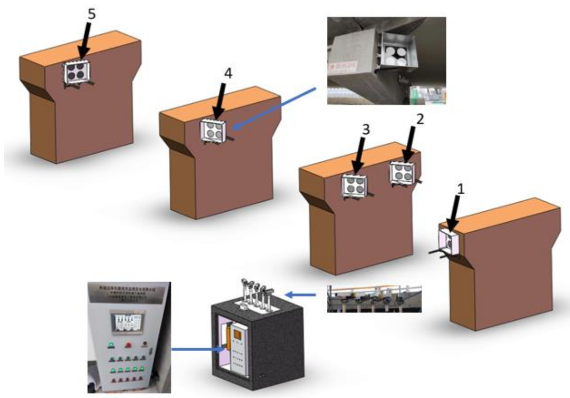

Figure 6: Field device layout diagram

When a load is applied to the highway bridge, the further the distance, the higher the requirement for monitoring accuracy. Therefore, the data from measurement point 5 is analyzed and summarized. The monitoring data before and after a vehicle passes over the highway bridge is used for local comparison, as shown in Figure 7.

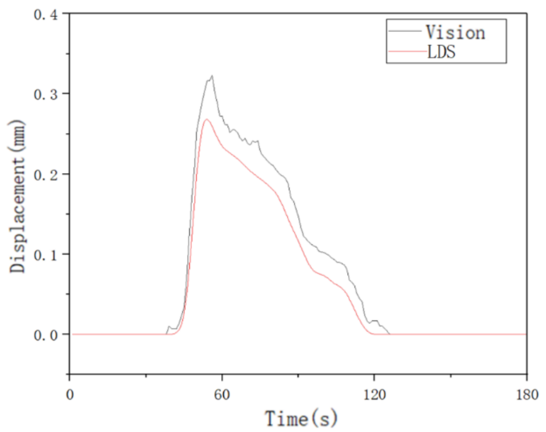

Figure7: Bridge pile foundation mark 5

From Figure 7, it can be observed that both methods exhibit consistent trends in monitoring the settlement and displacement of the bridge pile foundation, indicating the high reliability of the machine vision-based monitoring system. When a vehicle passes through monitoring point 5, the LDS measures a maximum change of 0.27mm in the bridge pile foundation. Meanwhile, the machine vision-based monitoring system detects a maximum change of 0.32mm in the bridge, with an error of 0.11mm. This small error demonstrates strong accuracy in monitoring the settlement and displacement of highway bridge pile foundations.

3.3 Long-term Displacement Monitoring

The experimental setup is arranged as shown in Figure 6. The experimental data were collected over a period from 0:00 to 24:00 on a certain day. To better simulate real-world monitoring conditions, data were collected at intervals of every 5 minutes.

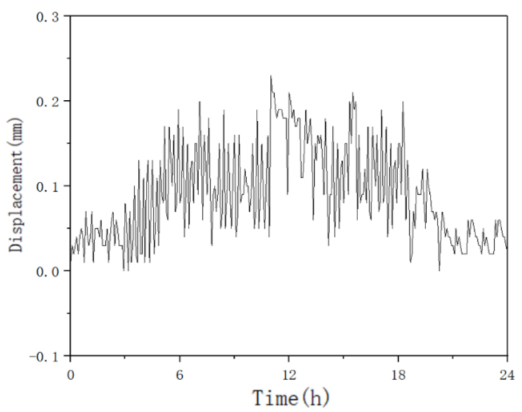

Figure 8: Long-term displacement monitoring results

From the figure, it can be seen that the machine vision-based highway bridge settlement monitoring system exhibits stable long-term monitoring performance with high sensitivity. During monitoring, the displacement data show a jagged trend, but the magnitude of displacement decreases noticeably when vehicle traffic decreases at night. The settlement displacement monitoring data at 0:00 and 24:00 are nearly identical, indicating that the hardware infrastructure can adapt well to long-term operation. This method demonstrates excellent performance for long-term monitoring.

4. Conclusion

1) This method can capture structural displacement changes in highway bridge pile foundations during deep excavation, providing effective support for damage assessment, condition evaluation, and assessing the impact of excavations on bridge pile foundations.

2) The Python program used in the article effectively transfers data to the IoT platform, allowing personnel to access highway bridge pile settlement data and overall linear changes in bridge structures at any time and from any location.

3) For highway bridges requiring focused attention on pile settlement changes, the integrated system can meet long-term monitoring needs, providing real-time information on bridge settlement and offering recommendations and guidance for manual monitoring and bridge maintenance.

Therefore, this method enables non-contact real-time monitoring of highway bridge pile displacements, with advantages such as high efficiency, fast detection speed, and stable monitoring. It can perform ideally near highway bridges during construction activities.

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