High precision slope deformation monitoring by UAV with industrial photogrammetry

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Abstract. As an important basis for quality and safety assessment during the service of large-scale structures, deformation monitoring has received extensive attention in both civil and mechanical engineering. Although many methods of deformation monitoring have been developed, measurement accuracy, implementation cost, and convenience are still the critical barriers that prevent their wide application, especially for side slopes measuring thousands of kilometres. This work proposes a high-accuracy, low-cost, and automatic slope deformation monitoring method that can be used with unmanned aerial vehicles (UAVs) and industrial photogrammetry technology. Specifically, a UAV is equipped with a high-quality industrial camera, the slope surface is arranged with artificial markers, and five markers in the stable area near the bottom of the slope are pre-calibrated to define a local 3D coordinate system. The flight of the UAV, detection of the markers, and determination of their 3D coordinates are all completed automatically. To test this method, a monitoring experiment of the cross section of the slope of the Chinese South-to-North Water Diversion Project (CSNWDP) was performed. It is shown that this method improves measurement accuracy by an order of magnitude over conventional aerial photogrammetry, and both the horizontal and vertical displacements are measured accurately within 2~3 mm.

1. Introduction
Deformation monitoring of large-scale outdoor structures is widely applied in civil and military engineering projects[1]. The monitoring accuracy, cost, and convenience are largely determined by the monitoring methods applied. Therefore, automated monitoring methods with high accuracy and low cost are of great importance to large-scale engineering projects.

Research of slope deformation monitoring has been an important topic in both academia and industry[2]. In recent years, the safety maintenance of large-scale water diversion projects and high-speed railway projects has placed higher requirements on the efficiency and accuracy of slope deformation monitoring methods. For example, the Chinese South-to-North Water Diversion Project (CSNWDP) is the largest water conservancy project in the world (Figure. 1), directly benefiting more than 100 million people. CSNWDP consists of three main lines: eastern, middle, and western, where the middle line is as long as 1,432 km. As the middle line passes through an expansive soil section, the problem of slope stability is important. The deformation monitoring of the slope is needed to ensure the
safe operation of the entire CSNWDP. Therefore, a low-cost and high-accuracy monitoring method is of great value and significance for the slope monitoring of such projects.

Conventional slope deformation monitoring mainly includes point monitoring and surface monitoring. Total stations, levelling instruments, and GNSS are widely applied in point monitoring. By building observation piers on the slope, the deformation of discrete points instead of the whole slope is measured by total stations or levels[3,4]. In this way, the measurement accuracy is high, and the deformation sites are clearly expressed. But this method has some disadvantages, such as high labour intensity, time consumption, and lack of deformation detail. GNSS can achieve automatic monitoring, but the equipment is expensive, and its measurement accuracy is relatively low[5,6]. Synthetic aperture radar (SAR) interferometry[7,8] and 3D laser scanning[9] are the main surface monitoring methods. Satellite SAR technology has the advantages of low cost and wide coverage, but it cannot completely replace other monitoring methods because of its low measurement accuracy. Using ground-based SAR or a 3D laser scanner could obtain the deformation with high accuracy. However, due to the high price of the devices and the difficulty of transporting, relocating, and installing the monitoring stations, they are difficult to implement in large-scale projects such as CSNWDP.

Unmanned aerial vehicle (UAV) photogrammetry has become a popular method for large-area mobile measurements due to its flexibility, low cost, and automation, and it has been studied and applied to monitor landslide or slope deformation[10-18]. The above-cited studies investigated the applicability and accuracy of UAV photogrammetry methods, and displacements were achieved by comparing the differences between the 3D point cloud coordinates or digital elevation models obtained by periodic flights. However, the current accuracy of UAV photogrammetry methods is at the centimetre level and cannot meet the accuracy requirements of deformation monitoring in most cases. The main reasons are as follows: 1) the accuracy of GPS positioning on UAVs is relatively low for deformation monitoring, even if on-board receivers capable of real-time kinematic (RTK) positioning are used; 2) the camera carried by a UAV usually has large distortion and noises in imaging; and 3) sometimes the surface texture of the slope is not rich enough.

In this work, we propose a slope deformation monitoring method that combines a UAV and industrial photogrammetry technology to improve the measurement accuracy. By equipping the UAV with high-quality industrial cameras, setting markers on the slope, and self-defining a high-accuracy local 3D coordinate system, this method can increase the accuracy to the millimetre level. An experiment of slope deformation monitoring was conducted to demonstrate the performance of the proposed method. The rest of this paper is organized as follows. Section 2 explains the proposed method in detail. Section 3 reports the experiment results and analysis. Section 4 summarizes our conclusions.
2. Methodology
In this method, ground markers are first arranged in the area to be monitored. An industrial camera on a UAV is used to collect images, which are processed by a series of algorithms, such as marker location, structure from motion (SfM), and bundle adjustment (BA), to obtain high-accuracy 3D coordinates of the markers. Finally, by comparing 3D coordinates of the markers obtained by flights before and after the deformation, we can determine the displacements of the monitored area.

2.1 Setting markers
In industrial photogrammetry, artificial markers such as coded or uncoded targets can be used to improve accuracy and enrich surface texture. Usually, a direct assessment of precision below the pixel resolution of the sensor would be difficult from points marked manually or generated automatically by SIFT[19]. But the centres of artificial markers can be estimated precisely, well below 1/10th of a pixel[20,21]. In this method, circular markers are set on the slope as reference points. The markers are made of retro-reflective material that can reflect light toward the source from a much wider angle than that of reflective material[22].

The deformation for a large-scale linear-type engineering project such as CSNWDP can be mechanically approximated as a plane strain problem. Artificial markers can be sequentially set along the intersection line of the slope with the cross section perpendicular to the direction of the water flow. Two lines of ordered markers form a monitoring area of the slope, as shown in Figure. 2. The distance between neighbouring markers is determined according to the length and height of the slope, as well as the camera and flight parameters.

A high-precision coordinate frame is placed in the monitoring region to define a local 3D coordinate system, as shown in Figure. 2. The coordinate frame consists of five coded markers. The X-axis is the line linking markers 1 and 2, the Y-axis links markers 3 and 4, and the Z-axis is determined by the right-hand rule. Marker 5 is a checkpoint of the defined 3D coordinate system. The coordinate frame can be pre-calibrated by industrial photogrammetry with the accuracy of 0.05 mm, meeting the requirements to define a high-accuracy local coordinate system. The coordinate frame is fixed in the stable area near the bottom of the slope. The above definition of the coordinate frame and coordinate system is recommended but not required. Any three or more markers in the stable area of the slope can be pre-calibrated to define a local 3D coordinate system.

2.2 Automatic image collection by UAV and industrial camera
After the setting of markers, high-quality images are collected by the UAV equipped with an industrial camera. These cameras outperform ordinary cameras in three aspects. 1) Higher efficiency of image collection. Since industrial cameras have short shutter times and no motion blurring of the captured image, there is no need to hover to take pictures during flight. 2) Lower imaging noise. Figure. 4 shows some of the images of a light-reflecting marker taken from industrial and ordinary cameras. We can see that the noise of the ordinary camera can reflect the grey value on the images and bring more errors when locating the centre of the marker. 3) Smaller imaging distortion.

The industrial camera used in this paper is a CMOS camera, with 4,096×3,000 pixels over a 14.13 mm×0.35 mm sensor, paired with a manual-focus 50-mm lens. The shutter time is up to 2 µs, and the temporal dark noise is less than 2.5 e-. A self-assembled UAV was used to carry the industrial camera, as shown in Figure. 3; its no-load lifetime is longer than 40 min. Parameters such as the elevation of the flight height, camera angle, and overlapping ratios can be optimized to maximize the efficiency of the system while meeting the accuracy requirements of deformation monitoring. After the parameters are set, the UAV can fly automatically according to a planned path and control the industrial camera to take photos during the flight to realize automatic image collection.

2.3 Image data processing
After image collection, the markers on each image are recognized and located. Then software is used to roughly obtain the 3D coordinates of the markers, the intrinsic and extrinsic camera parameters, and the
camera calibration parameters, which are further optimized by self-calibration bundle adjustment. Finally, the 3D displacements of the monitoring area are achieved by comparing the differences between the 3D coordinates of the markers before and after deformation.

The detection of characteristic points or edges from imaged object structures is a frequent task in photogrammetric image processing. Here, the prerequisites for high-precision measurement are detection of the edges of the circular markers from the images and locations of their centres[23-25]. The classical Canny edge detection operator, which only produces single-pixel edges, is highly recommended since it is suitable for extracting the edges of such circular markers. After processing by the Canny operator, a binary image consisting of discrete edge pixels and noise is further processed through an edge tracking algorithm or boundary closure algorithm to obtain the closed edge of the marker. Then the false markers on the image are removed by the ellipse test of its closed edges.

After determining the edge of the marker, the 2D coordinates of the marker centre in the image coordinate system can be calculated. This paper uses the grey-weighted centroid algorithm to obtain the position of the marker centre with accuracy at the sub-pixel level. The algorithm is commonly used for high-precision positioning of centre-symmetric targets such as circles, ellipses, and rectangles. The grey-weighted centroid algorithm calculates the weighted average of all pixel coordinates in the edge of the marker, with the grey value of a pixel as its weight. The calculation formula is

\[
\begin{align*}
    x_0 &= \frac{\sum u W_{u,v}}{\sum W_{u,v}}, \\
    y_0 &= \frac{\sum v W_{u,v}}{\sum W_{u,v}},
\end{align*}
\]

where \((x_0, y_0)\) is the position of the marker centre in the image coordinate system; \(W_{u,v}\) is the weight, which is the grey value of pixel \((u, v)\); and \(\Omega\) is the region in the edge of the marker.

Figure 3. Self-assembled UAV with an industrial camera.

Since the grey value of each pixel in the edge of the marker directly serves as the weight to calculate the position of the marker centre, this algorithm has high requirements on the image quality. Especially
for an imaged marker with few pixels, the noise should be suppressed, or the accuracy of the position will be seriously affected. Therefore, the grey-weighted centroid algorithm for images captured by an industrial camera can locate the marker centre more accurately than an ordinary camera.

The key algorithm of high-precision photogrammetric data processing is the self-calibration bundle adjustment, by which the image point coordinates are taken as the observation values, and the 3D coordinates of points on object structures, intrinsic and extrinsic camera parameters, and camera calibration parameters are simultaneously calculated by the bundle adjustment (BA) algorithm[26-28]. Since the equations solved in BA have strong nonlinearity, the initial values of the unknown parameters should be given before the linearization of the equations. The initial values of the camera calibration parameters can be pre-calibrated using a checkerboard pattern. The initial values of other unknown parameters can be obtained through an SfM algorithm or software, which is commonly used to estimate 3D structures from 2D image sequences captured by a motion camera. In our case, for deformation monitoring, the calculated value of markers in previous flights can be directly used as initial values in image data processing.

Assume that \( n \) 3D points are seen in \( m \) images and denote the projection of the \( i \)-th image of a point \( X_j \) on the 3D object space as \( x_{ij} \). BA is equivalent to finding the set of parameters that most accurately predicts the locations of the observed \( n \) points in the set of \( m \) available images. Without loss of generality, assume that each camera \( i \) is parameterized by a vector \( a_i \), which consists of the intrinsic and extrinsic camera parameters and the camera calibration parameters. BA minimizes the reprojection error with respect to all 3D points and camera parameters, i.e., the least-squares reprojection error

\[
\min_{a_i, x_j} \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} \left\| Q(X_j, a_i) - x_{ij} \right\|^2 .
\]  

(2)

Since not every 3D point is imaged on all cameras, \( c_{ij} \) is a variable such that \( c_{ij} = 1 \) if the point \( X_j \) is seen on the \( i \)-th image, while \( c_{ij} = 0 \) if not. \( Q(X_j, a_i) \) is the predicted projection of point \( X_j \) on image \( i \).

To facilitate the programming calculation, \( n \) 3D points \( X_j \) and \( m \) parameters \( a_i \) are mapped to a vector \( U = [X_1^T, X_2^T, ..., X_n^T, a_1^T, a_2^T, ..., a_m^T] \). If the predicted projection vector is denoted by \( \bar{x} = f(U) \), then the above equation is rewritten as

\[
\min \left\| f(U) - x \right\|^2 ,
\]  

(3)

where

\[
x = [x_{11}^T, x_{12}^T, ..., x_{1m}^T, x_{21}^T, x_{22}^T, ..., x_{2m}^T, ..., x_{n1}^T, x_{n2}^T, ..., x_{nm}^T]
\]  

is the vector of observed projections of all images for all points.

The reprojection error minimization can be calculated by the Levenberg-Marquardt (LM) algorithm. The weighted incremental iterative equation (normal equation with weights) in the LM algorithm is

\[
(J^TPJ + \mu I)\delta_U = J^TP\varepsilon ,
\]  

(4)

where \( \delta_U \) is the increment of the unknown parameter vector \( U \), \( \varepsilon = \bar{x} - x \) is the vector of the reprojection error, \( J = \partial f / \partial U \) is the Jacobian matrix, \( P \) is the weight matrix, \( \mu \) is the damping coefficient, and \( I \) is the unit matrix. Since different 3D points and cameras have little influence on each other, the coefficient matrix of the linearized equation presents a sparse structure. With this sparse property, sparse bundle adjustment (SBA) using the LM algorithm is already a comparatively mature method to solve the equation[28].
In the process of deformation monitoring, the coordinate frame is placed in a relatively stable area. Markers on the coordinate frame are pre-calibrated, with initial accuracy up to 0.05 mm, and can be used as high-accuracy control points. The initial values of other markers are obtained by SfM or are set at their calculated values before deformation, with an accuracy at the millimetre or centimetre level, so different weight values must be assigned to different object markers. The weight plays a key role in the bundle adjustment calculation. The magnitude of the weight directly affects the convergence speed and even the convergence accuracy of the bundle adjustment. To better test the weights, only the weight of one observation value is changed at each calculation, and the calculation accuracy and iteration number are analysed to find the appropriate weight.

3. Experiment implementation and results

A deformation monitoring experiment for the slope of CSNWDP was performed. The procedure is shown in Figure 4. After a site survey, the coordinate frame and markers were set on the slope, with three markers used as checkpoints. The flight path of the UAV in the experimental area was planned, and the first image collection was performed. Then all the markers on the slope were moved several millimetres, and the displacements of the three checkpoints were recorded before collecting images. This procedure was repeated 17 times; hence, the image data were collected 18 times. Finally, the 18 groups of images were processed by a computer, the displacements of the three checkpoints were calculated, and their accuracy was analysed.

3.1. Experimental processes

The experiment on a monitoring section of an artificial canal slope located at CSNWDP was performed, where the area of experimental region the is 15 m×45 m. A total of 40 markers were placed on the monitoring section, which could be divided into three parts: 1) Two lines of ordered markers were set on the drainage ditches of the slope, as shown in Figure 5, where the distance between neighbouring markers was about 2 m along the line, and the distance between the lines was 3 m; 2) The coordinate frame consisted of five markers fixed in the stable area near the bottom of the slope, which remained constant during the experiment; 3) Two checkpoints and one checkpoint were set on the top and middle of the slope, respectively. As shown in Figure 6, the three checkpoints were placed on the XYZ three-axis mobile platform, which had a horizontal control accuracy of 0.03 mm and an elevation control accuracy of 0.1 mm. By using the platform, the 3D displacements of the checkpoints could be recorded accurately to compare with the calculated displacements.

The UAV and industrial camera used in the experiment were discussed in Section 2.2. Since the shutter time of the camera was very short, images could be collected during flight without hovering. The camera was set to automatically capture three images per second during the flights. The UAV flew in terrain-following mode along the line of markers. These flights (see Figure. 7) were carried out from heights of 35 m and 45 m. About 300 images were collected during each flight. Both the forward and side overlapping ratios were greater than 80%.
After each flight, we slightly moved all the markers except for the five markers of the coordinate frame and accurately recorded the displacements of the three checkpoints. To ensure that the simulated displacements roughly agreed with the characteristics of plane strain of the slope, the markers were moved a few millimetres in the plane perpendicular to the direction of the water flow. They were moved horizontally toward the bottom of the slope, and downward. For convenience in comparing results, the horizontal and vertical displacements of the three checkpoints were -2 mm before even-numbered flights and -3 mm before odd-numbered flights. The markers were moved 17 times, and image data were collected 18 times. The total horizontal and vertical displacements of the three checkpoints were -42 mm.

The collected image data were processed automatically by a series of algorithms such as location of markers, SfM, and BA, as shown in Section 2.3. Some commercial software, such as ContextCapture Smart3D, Pix4D Mapper, and Agisoft Metashape, includes these algorithms. We used Agisoft Metashape to evaluate the images obtained from UAV flights and to produce the photogrammetry outcomes. Figure 8 shows the 3D point cloud of the monitoring region, and the 3D coordinates of the centre of the markers are obtained from image data processing. By comparing the differences between the 3D coordinates of the markers obtained by all the flights, we obtained the displacements of the markers (including the three checkpoints) over the whole experiment.

3.2. Experimental results and analysis
The calculated displacements of the three checkpoints were compared with the recorded displacements. The displacement curves are shown in Figure 9, and the horizontal and vertical displacement data are summarized in Tables 1 and 2, respectively. The root mean square error (RMSE) was used to determine the differences between calculated and recorded displacements, as shown in Table 3. We can see that the average RMSEs of the horizontal and vertical displacements were 1.7 mm and 2.3 mm, respectively. Both the horizontal and vertical displacements were measured accurately within 2~3 mm, satisfying the requirements of slope deformation monitoring.
Figure. 9 Comparison of horizontal and vertical displacements of the three checkpoints during the experiment.

Table 1 Recorded and calculated horizontal displacements of the three checkpoints (mm).

| Movement number | Checkpoint 1 Recorded displacement | Checkpoint 1 Calculated displacement | Checkpoint 1 Error | Checkpoint 2 Recorded displacement | Checkpoint 2 Calculated displacement | Checkpoint 2 Error | Checkpoint 3 Recorded displacement | Checkpoint 3 Calculated displacement | Checkpoint 3 Error |
|-----------------|----------------------------------|------------------------------------|------------------|----------------------------------|------------------------------------|------------------|----------------------------------|------------------------------------|------------------|
| 1               | -2.0                             | -3.2                               | -1.2             | -2.7                             | -0.7                               | -2.5             | -0.5                             |
| 2               | -5.0                             | -4.3                               | 0.7              | -3.5                             | 1.5                                | -3.5             | 1.5                             |
| 3               | -7.0                             | -7.9                               | -0.9             | -6.5                             | 0.5                                | -5.7             | 1.3                             |
| 4               | -10.0                            | -9.7                               | 0.3              | -8.8                             | 1.2                                | -7.5             | 2.5                             |
| 5               | -12.0                            | -14.3                              | -2.3             | -12.9                            | -0.9                               | -11.5            | 0.5                             |
| 6               | -15.0                            | -16.1                              | -1.1             | -16.3                            | -1.3                               | -15.2            | -0.2                             |
| 7               | -17.0                            | -20.0                              | -3.0             | -19.7                            | -2.7                               | -19.2            | -2.2                             |
| 8               | -20.0                            | -22.0                              | -2.0             | -22.2                            | -2.2                               | -21.5            | -1.5                             |
| 9               | -22.0                            | -23.8                              | -1.8             | -24.7                            | -2.7                               | -23.6            | -1.6                             |
| 10              | -25.0                            | -25.3                              | -0.3             | -26.2                            | -1.2                               | -25.7            | -0.7                             |
| 11              | -27.0                            | -28.1                              | -1.1             | -28.3                            | -1.3                               | -26.3            | 0.7                              |
| 12              | -30.0                            | -29.6                              | 0.4              | -29.9                            | 0.1                                | -27.4            | 2.6                              |
| 13              | -32.0                            | -34.2                              | -2.2             | -30.7                            | 1.3                                | -33.6            | -1.6                             |
| 14              | -35.0                            | -38.4                              | -3.4             | -36.5                            | -1.5                               | -35.5            | -0.5                             |
| 15              | -37.0                            | -38.0                              | -1.0             | -39.3                            | -2.3                               | -35.7            | 1.3                              |
| 16              | -40.0                            | -38.7                              | 1.3              | -39.4                            | 0.6                                | -37.2            | 2.8                              |
| 17              | -42.0                            | -39.2                              | 2.8              | -40.2                            | 1.8                                | -40.2            | 1.8                              |
Table 2 Recorded and calculated vertical displacements of the three checkpoints (mm).

| Movement number | Recorded displacement | Calculated displacement | Error | Calculated displacement | Error | Calculated displacement | Error |
|-----------------|-----------------------|-------------------------|-------|-------------------------|-------|-------------------------|-------|
| 1               | -2.0                  | -3.2                    | -1.2  | -2.4                    | -0.4  | -2.7                    | -0.7  |
| 2               | -5.0                  | -6.5                    | -1.5  | -5.2                    | -0.2  | -3.5                    | 1.5   |
| 3               | -7.0                  | -8.7                    | -1.7  | -7.0                    | 0.0   | -7.3                    | -0.3  |
| 4               | -10.0                 | -10.2                   | -0.2  | -10.7                   | -0.7  | -10.0                   | 0.0   |
| 5               | -12.0                 | -12.8                   | -0.8  | -14.5                   | -2.5  | -14.1                   | -2.1  |
| 6               | -15.0                 | -18.6                   | -3.6  | -18.5                   | -3.5  | -17.0                   | -2.0  |
| 7               | -17.0                 | -21.1                   | -4.1  | -22.1                   | -5.1  | -20.6                   | -3.6  |
| 8               | -20.0                 | -23.2                   | -3.2  | -24.5                   | -4.5  | -22.9                   | -2.9  |
| 9               | -22.0                 | -20.7                   | 1.3   | -23.8                   | -1.8  | -22.1                   | -0.1  |
| 10              | -25.0                 | -23.0                   | 2.0   | -27.2                   | -2.2  | -26.7                   | -1.7  |
| 11              | -27.0                 | -25.8                   | 1.2   | -29.2                   | -2.2  | -28.4                   | -1.4  |
| 12              | -30.0                 | -29.7                   | 0.3   | -31.3                   | -1.3  | -31.3                   | -1.3  |
| 13              | -32.0                 | -29.9                   | 2.1   | -32.7                   | -0.7  | -33.8                   | -1.8  |
| 14              | -35.0                 | -33.4                   | 1.6   | -38.7                   | -3.7  | -35.9                   | -0.9  |
| 15              | -37.0                 | -35.6                   | 1.4   | -41.3                   | -4.3  | -40.7                   | -3.7  |
| 16              | -40.0                 | -36.5                   | 3.5   | -42.2                   | -2.2  | -42.2                   | -2.2  |
| 17              | -42.0                 | -39.6                   | 2.4   | -43.7                   | -1.7  | -43.9                   | -1.9  |

Table 3 RMSE values of the difference determined from calculated and recorded displacements.

| Direction | Checkpoint 1 | Checkpoint 2 | Checkpoint 3 | Average |
|-----------|--------------|--------------|--------------|---------|
| Horizontal| 1.8          | 1.6          | 1.6          | 1.7     |
| Vertical  | 2.2          | 2.7          | 2.0          | 2.3     |

4. Conclusion
This paper presents a new methodological solution for slope deformation monitoring using a UAV and industrial photogrammetry technology. First, artificial markers are fixed on the slope surface according to the deformation characteristics of the slope, and five markers in the stable area near the bottom of the slope are pre-calibrated to define a local coordinate system. A UAV equipped with a low-noise, small-distortion industrial camera collects image data regularly. Images are processed by a series of algorithms (such as marker location, SfM, and BA) to obtain high-accuracy 3D coordinates of the markers. By comparing the markers’ coordinates before and after the deformation of the slope, the displacement of the markers in the monitored area can be obtained. An experiment of monitoring the cross section of the slope of CSNWDP was performed. The results show that both the horizontal and vertical displacements were measured accurately within 2~3 mm, satisfying the requirements of slope deformation monitoring. In conclusion, using a UAV with industrial photogrammetry technology, the method is capable of conveniently monitoring the deformation of large-scale structures with a lower cost and higher accuracy than conventional methods.

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