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Research on the Application of UAV Tilt Photography Image Processing Based on Image Recognition Technology in Civil Engineering Disaster Monitoring

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Abstract The real-time perception requirements for surface deformation and moving targets in civil engineering disaster monitoring are increasing day by day. This paper proposes an image processing method for unmanned aerial vehicle (UAV) oblique photography that integrates multi-view 3D modeling and an improved deep learning network. A high-precision three-dimensional surface model is constructed through multi-view image fusion, point cloud filtering optimization and error calibration techniques. Combined with the improved DeeplabV+ network, an image segmentation model including multiple modules such as the encoding network, spatial pyramid module and decoding network is constructed to achieve the accurate segmentation of landslide targets. The results show that the accuracy of the method proposed in this paper in the image processing of objects related to different civil engineering disasters reaches 86.57%, 88.54%, 92.32%, 88.46%, and 89.75% respectively, which is much higher than that of the comparison methods. In disaster monitoring, the application of the method in this paper can increase the identification rate of hidden danger points to 98%, advance the early warning time by an average of 8 days, and reduce economic losses by 1.6 million yuan.

Index Terms unmanned aerial tilt photography, three-dimensional modeling, multi-view fusion, DeeplabV3+ network, disaster monitoring

I. Introduction

Civil engineering disasters occur from time to time in the course of human development and often cause great losses. Civil engineering disasters occur for a variety of reasons. But in the final analysis, it can be roughly divided into two categories: reasons related to the natural environment, is man-made forces can not control and can not be changed, common phenomena are earthquakes, floods, storms and other phenomena, resulting in mudslides, ground collapses, tsunamis, water contamination, power failures [1]-[3]. Human-related causes, which are caused by objective developments, commonly include timber corrosion, displacement of buildings, aging, foundation instability, etc., resulting in significant property damage and personal injury [4]. Civil engineering is affected by natural weather, especially in the construction process is very easy to encounter disasters, in order to minimize the degree of harm caused by disasters, not only to clarify the disaster, the type of disaster and its characteristics, but also on the factors that can not be defended against the ability to make an objective analysis of the ability to prevent, accordingly accurately formulate an effective defense countermeasures [5]-[8]. And disaster monitoring is a prerequisite for disaster defense, is the key initiative for disaster reduction. The existing conventional monitoring technology is difficult to meet the waterproof and moistureproof, anti-electromagnetic interference and real-time monitoring and other civil engineering monitoring requirements, and there is a coverage of the blind spot, engineering damage detection accuracy is low, disaster response lag [9]-[12].

Compared with traditional photography technology, UAV oblique photography technology has obvious advantages, because of its advantages of fast mapping and high accuracy, it is widely used in topographic map surveying and mapping, construction engineering surveying, water conservancy and hydropower surveying and other fields, and has achieved good application results [13]-[16]. In addition, compared with the traditional basic aerial photography method, UAV tilt camera technology realizes efficient monitoring and three-dimensional construction of multi-dimensional angle shooting, and it can still obtain high precision images under complex weather conditions [17], [18]. Therefore, in civil engineering disaster monitoring, the application of UAV tilt photography technology has a wide range of prospects.

This paper focuses on the image processing method of UAV tilt photography technology in civil engineering disaster monitoring. The key steps of multi-view image fusion and 3D modeling are analyzed, and the effects of point cloud density and distribution on model accuracy are discussed. An error calibration framework based on ground control points is proposed, combining global parameter calibration and local interpolation optimization to reduce systematic errors. For the segmentation of disaster motion targets, a hybrid strategy of background difference method and morphological denoising is synthesized, and an improved DeeplabV3+ network is constructed to enhance the image feature extraction capability. Compare the image processing accuracy of different methods, and set up a UAV monitoring program to verify the performance advantages of the method in this paper.

II. Analysis of drone tilt-photo image processing technology

This chapter analyzes the UAV tilt-shot image processing method based on image recognition technology and studies its role in civil engineering disaster monitoring.

II. A. Technical realization of tilt photogrammetry

II. A. 1) Multi-view fusion and 3D modeling techniques for tilted images

Multi-view fusion is the core technology of image processing in UAV inclined photogrammetry, which aims to utilize the overlapping areas between images to extract key points and generate high-precision point cloud data. The first step of image fusion is image matching, in which the feature points of the image are extracted by a feature point matching algorithm (e.g., SIFT), and the matching and filtering operations of the feature points are carried out in order to eliminate the noise points and anomalies. The level of matching accuracy directly affects the completeness and accuracy of the point cloud data. After the multi-view image fusion generates the point cloud, the key steps of 3D modeling are point cloud filtering, sparse reconstruction and texture mapping. The point cloud filtering stage removes spurious noise points and retains high-confidence points to improve the modeling quality. The reconstruction uses geometric constraints to extract major terrain structures and generate a preliminary terrain skeleton. The texture mapping stage maps the texture data from the image onto the surface of the point cloud model, making the model more realistic and detailed. The density and distribution of the point cloud in the 3D modeling process have a significant impact on the model accuracy. In civil engineering disaster monitoring areas with complex terrain, the point cloud density should reach 8500 to 11000 points/m² to ensure the spatial resolution and detail portrayal ability of the model. The combination of multi-view fusion and 3D modeling technology improves the accuracy of the terrain model and also optimizes the visualization of the data, providing a high-quality data base for civil engineering disaster monitoring area measurements.

II. A. 2) Calibration of measurement accuracy and error optimization methods

The calibration of the measurement accuracy takes the ground control points as the reference and compares the coordinate differences between the control points and the model points to calculate the error distribution of the model. The sources of error are mainly image matching error, UAV route planning error and point cloud generation error. The image matching error is related to the distribution density of the feature points, and the error is usually larger in sparsely distributed areas. The UAV route planning error, on the other hand, is directly related to the degree of image overlap, and too low an overlap will lead to local data loss in the model. The process of error optimization includes calibration of systematic error and adjustment of random error. The systematic error can be calibrated by adjusting the global transformation parameters such as the rotation angle and translation correction of the model. The optimization of random error requires the use of multiple interpolation and surface fitting techniques, etc. to reduce the deviation of the local model. The error optimization formula is as follows:

$$E=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left(x_i-x_i'\right)^2+\left(y_i-y_i'\right)^2+\left(z_i-z_i'\right)^2\right)} \tag{1}$$

where, E represents the overall error, n is the number of control points, x_i, y_i, z_i is the control point coordinates, and $(x_{i'}, y_{i'}, z_{i'})$ is the model point coordinates. The optimized error can usually be controlled within the millimeter level, which significantly improves the accuracy and reliability of the model. The accuracy calibration and error optimization provide a guarantee for the accuracy of the model and lay a solid foundation for subsequent data analysis and application.

II. B.Image Processing in Motion Surveillance Systems for Civil Engineering Disasters

II. B. 1) Segmented monitoring of disaster movement targets

In the design of civil engineering disaster motion monitoring system, for the scene sequence processing and analysis of video images, the key points are the segmentation and detection of moving targets, the denoising and labeling of images, and the final target tracking and confirmation of three aspects. The detection system extracts the motion targets in the video to remove noise and track the effective trajectory, and confirms the targets according to the characteristics of the disaster.

The civil engineering disaster motion target extraction system design uses a mixture of background difference method and median method, the most important thing in the method is to update the image in time and produce a fast response in the detection, the background image is initialized by the median method. The method requires a large number of computations of consecutive multi-frame images, the pixel gray value is the main calculation that depends on the background, so the background update algorithm is introduced to retain the median method, the detection of the current frame of the target is based on the updated background of the previous frame, updating the current frame to the next frame of the background, the use of formulas such as the following equation (2):

$$B_{k+1} = B_k + \alpha(f_k - B_k) \tag{2}$$

where B_{k+1} represents the image recognition value of the next frame after updating; B_k is the image recognition value of the current frame; f_k refers to the foreground recognition data of the current frame; and α is the updating weights, which are selected according to Equation (3).

$$\alpha = \alpha_1(1 - D_k) + \alpha_2 D_k \tag{3}$$

where, D_k refers to the difference pixel grayscale data of the video recognition image and the current image; α_1 and α_2 are the weighted parallel values before and after image recognition. After initializing the background to update the background and construct a new image recognition, if the median method ends at the beginning of the detection, the background constructed by the median method of Eq. (2) is chosen as B_k. Otherwise, continue to use Koller's method of computation, which ensures both the speed of the background update and the accuracy of the median method.

II. B. 2) Video image denoising and labeling

Video image recognition after processing on the target motion image appears to be differentiated, noise is detected in the motion target, there may be incomplete targets, there is no clear identification between moving objects, the test results need to be processed in order to obtain a complete and distinguishable target. Morphology simplifies the data of the video image, removes unrelated components and maintains the basic shape of the target. The most basic operation of morphology consists in first eroding and eliminating isolated points of the target in a small area, and then performing expansion calculations to fill the gaps in the small area. The selection of structural elements is the key to the mathematical morphology method of removing noise, detecting different sites and different areas of geohazards, noise and surface target size is not the same, so it is necessary to determine the noise as a structural composition according to the monitoring site. Morphological filtering processing to remove minor noise, connectivity gap filling, but the detection of the target still exists a large noise structure elements, the use of connectivity analysis can be used to solve the problem to a certain extent. The connectivity is pixels p, $q \in S$, assuming that all pixels on the path from p to q are contained in S, then p connects to q. In normal connectivity, the number of components that exceed a threshold value, its true connectivity region will be determined, and if the pixels in the connectivity region are less than a set threshold value, a twist is performed in the binary image pixel value region to remove the reversal noise in the background region. In addition, each connectivity component is labeled during connectivity analysis to distinguish different moving targets.

II. C.Landslide image segmentation based on improved DeeplabV3+ network

II. C. 1) General framework of the model

This section is to extract landslide features from the UAV tilt photography images of civil engineering landslide disasters that occurred in Linzhi, Tibet, however, due to the complex geological conditions and rainfall, the spectral features of its UAV tilt photography images are complex and variable, the size of the boundary contour changes irregularly, the difficulty of acquiring UAV tilt photography images is large, and the real-time nature of the disaster prediction is not high, therefore, an improved DeeplabV3+ network model, naming this algorithm as SEOLI.Figure 1 shows the structure of the algorithm model.

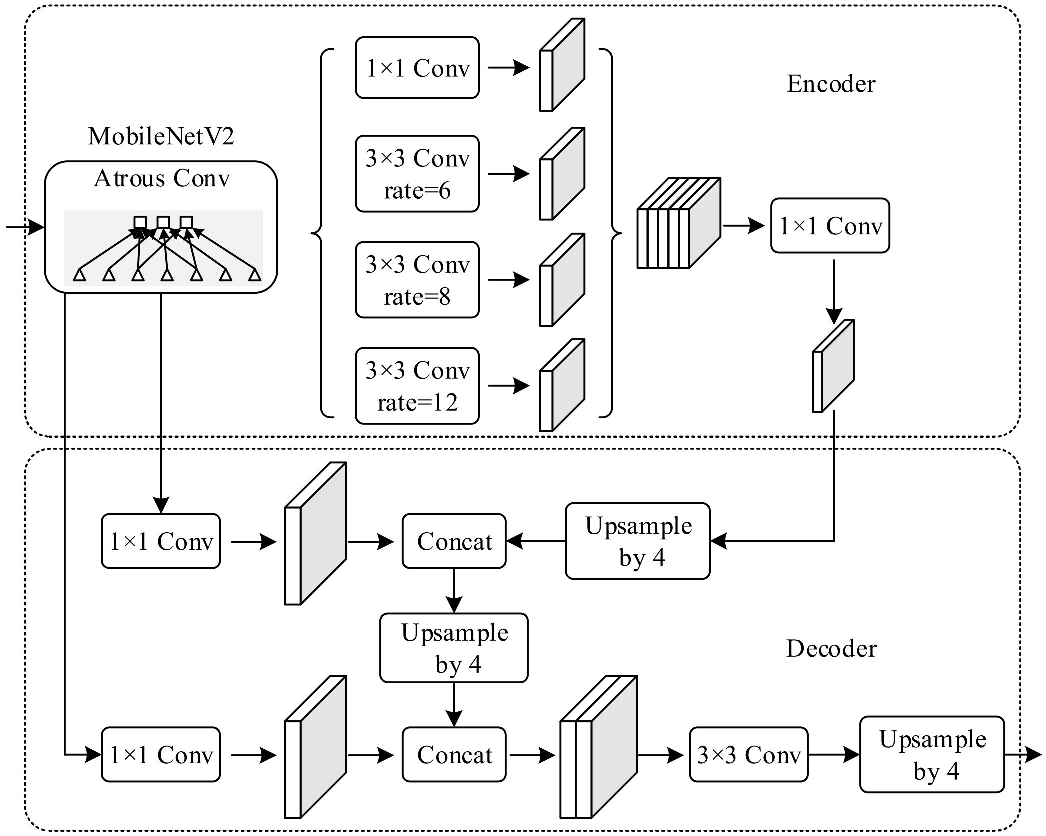

Figure 1: The algorithm model in this paper

In this paper, the improved DeeplabV3+ network semantic segmentation model is constructed using the Keras deep learning framework, which consists of three components: encoding network, spatial pyramid module, and decoding network. The UAV tilt photography landslide image is feature extracted through the structure of Figure 1 to obtain high-level image semantic information while retaining some of the low-level image detail information. The image space pyramid module is designed to improve the resolution of the feature map, and the cavity convolution with different cavity rates can generate a denser feature map. The output results of the image space pyramid module and the 3rd and 4th results of the MobileNetV2 coding module feature extraction are up-sampled and stacked to improve the details of the feature extraction, and after the stacked feature maps are up-sampled, the final inter-pixel classification is performed to obtain the results of landslide image extraction.

II. C. 2) Encoding and Decoding Module

The spatial pyramid module also performs feature extraction on the feature map, when the input image is convolved, the feature image elements are extracted at intervals, the extracted intervals are increasing and finally all the output images are merged, similar to the shape of a pyramid. As the method uses pooling and convolution with steps to adjust the spatial resolution of the feature map, increasing the ability to extract dense features discarding some edge detail information of the image, and the decoding part of the encoding-decoding module can repair the lost parts of the image sharp boundaries.

The features extracted by the coding module undergo 1×1 convolutional layers to change the number of channels, and after 3 times up-sampling, the feature map F1 is obtained; the two features extracted by the MobileNetV2 module undergo 1×1 convolutional layers respectively to obtain the new feature maps F2 and F3. F1 and F2 are connected together to obtain F4, which is then connected to F3 after 3 times up-sampling to obtain F5, and the classification result can be obtained after processing F5. Classification results can be obtained.

Assuming that the high-dimensional to low-dimensional mapping is $x \in \mathbb{R}^d$ to $z \in \mathbb{R}^p$, $p<d$, if the affine transformations are used to realize the high-dimensional to low-dimensional mapping

$$z = Wx \tag{4}$$

where $W \in \mathbb{R}^{p \times d}$ is the transformation matrix, and then transpose W to get

$$x = W^T z \tag{5}$$

It should be noted that Eq. (4) and Eq. (5) are not inverse operations; the two mappings are only formally transposed.

In a fully connected network, ignoring the activation function, the net input to layer $l+1$ is $z^{(l+1)} = W^{(l+1)} z^{(l)}$ when computed backward, and the error term in layer l is $\delta^{(l)} = \left(W^{(l+1)}\right)^T \delta^{(l+1)}$ when backpropagated.

When vector x is convolved with convolution kernel $w = [w_1, w_2, w_3]$, vector z is obtained as follows

$$\begin{aligned} z &= w \otimes x \\ &= \begin{bmatrix} w_1 & w_2 & w_3 & 0 & 0 \\ 0 & w_1 & w_2 & w_3 & 0 \\ 0 & 0 & w_1 & w_2 & w_3 \end{bmatrix} x \\ &= Cx \end{aligned} \tag{6}$$

If a mapping from z to x is to be realized, this can be achieved by transposing the

$$\begin{aligned} x &= C^T z \\ &= \begin{bmatrix} w_1 & 0 & 0 \\ w_2 & w_1 & 0 \\ w_3 & w_2 & w_1 \\ 0 & w_3 & w_2 \\ 0 & 0 & w_3 \end{bmatrix} z \\ &= rot150(w) \tilde{\otimes} z \end{aligned} \tag{7}$$

where $rot150(\cdot)$ denotes a rotation of 150 degrees.

From Eqs. (6) and (7), it can be seen that $z = w \otimes x$ and $x = rot180(w) \tilde{\otimes} z$ are also transposed relations, also known as inverse convolutions.

The transposed convolution also applies to 2D convolution, and Figure 2 gives two 2D convolutions and their corresponding transposed convolutions.

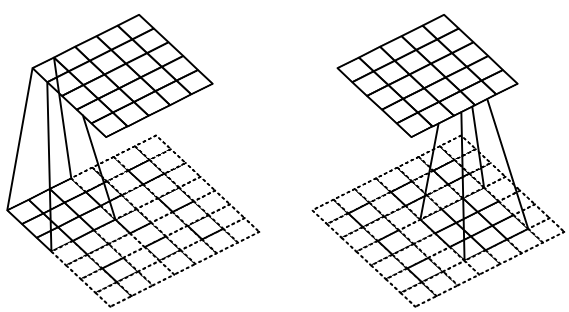

Figure 2: Transposed convolution corresponding to the two-dimensional convolution

III. UAV tilt-photography image-processing practices in civil engineering

This chapter compares the accuracy of UAV tilt photography and image processing and analyzes the effectiveness of civil engineering disaster monitoring using this technology.

III. A. Image processing and monitoring data acquisition

III. A. 1) Comparison of drone tilt-shot image accuracy

In order to verify the accuracy of the UAV tilt photography images based on image recognition technology, they are compared with the actual images captured by the sensors used in the civil engineering disaster information management department. Figure 3 shows the results of the displacement comparison between the sensor image and the UAV tilt-shift photography image at the same location from around March 8 to around May 28, 2024, with 10 days as a comparison period. Between the position information in the UAV tilt-photography image and the position information acquired by the sensor, the surface deformation varies only between 3 mm and 7 mm, and although there is still some difference between the two, the displacements are very small, indicating that monitoring images of the civil engineering disaster location can be obtained more accurately using UAV tilt-photography over a period of time that is stable.

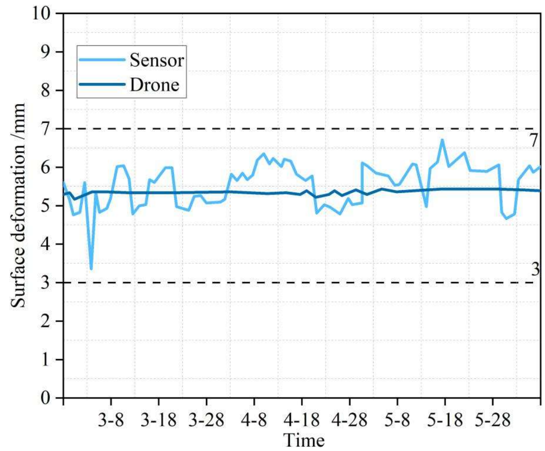

Figure 3: Displacement comparison result

III. A. 2) Calculation of three-dimensional surface variables

Further calculate the three-dimensional surface deformation error of the specific unmanned aerial vehicle oblique photogrammetry images to determine whether it can be used for the actual monitoring of landslide disasters in civil engineering. This paper compares the results of the A landslide monitoring point in Nyingchi Area, Tibet, obtained by photography from around March 8 to around May 28, 2024, with the actual results monitored by the sensors used by the civil engineering disaster information management department. Figure 4 shows the comparison results of the surface deformation in the X-axis direction. Figure 5 shows the comparison results of the surface deformation in the Y-axis direction. Figure 6 shows the comparison results of the surface deformation in the Z-axis direction. In the X-axis direction, the surface deformation of the oblique photography images of the unmanned aerial vehicle is between -6mm and 8.5mm, while the surface deformation of the sensor is between -4mm and 6mm. Overall, the difference is not significant. In the Y-axis direction, the surface deformation of the images obtained by both types of methods is between 1.2mm and 2.4mm. In the Z-axis direction, the surface deformation of the images collected by the sensor is stable at about 54mm, while the surface deformation of the images taken by the unmanned aerial vehicle (UAV) oblique photography fluctuates between 50mm and 60mm. From the comparison results of the three directions, it can be seen that the error between the three-dimensional surface deformation of the unmanned aerial vehicle (UAV) oblique photography and the three-dimensional surface deformation collected by the actual sensor is within the acceptable range. Combined with error optimization methods, etc., continuous improvement of three-dimensional modeling accuracy can also be achieved, which meets the monitoring requirements.

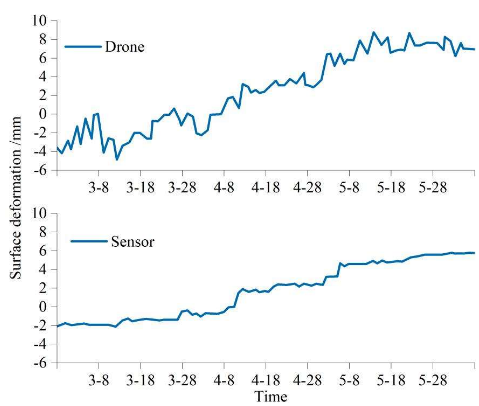

Figure 4: Comparison of surface deformation in the X-axis direction

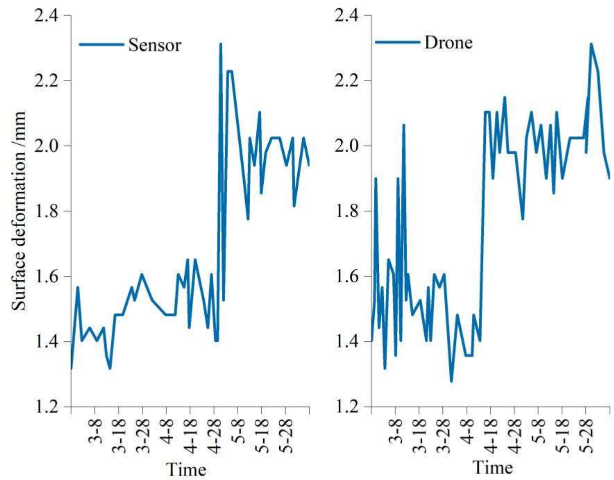

Figure 5: Comparison of surface deformation in the Y-axis direction

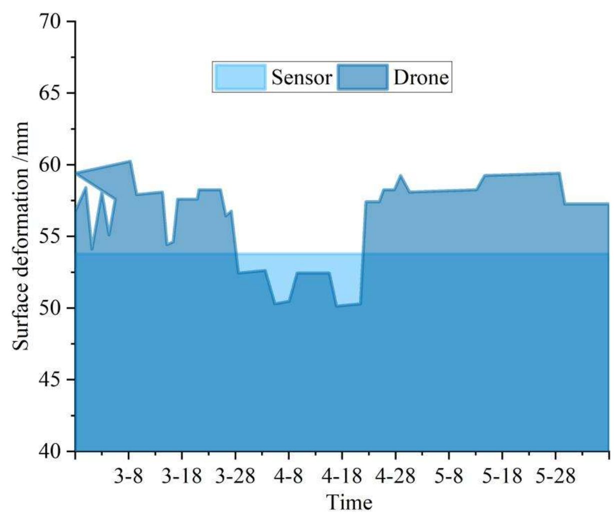

Figure 6: Comparison of surface deformation in the Z-axis direction

III. B. Comparison of image processing accuracy

III. B. 1) Comparison of image fusion accuracy

The civil engineering landslide process in this monitoring area on May 18 is used as an example to analyze the multi-view fusion processing accuracy of UAV tilted photography images based on image recognition technology. Figure 7 shows the UAV tilt photography images of the mountain vegetation before, during and after the landslide. Figure 8 shows the change process of mountain vegetation after multi-view fusion. After denoising and other processing, the mountain vegetation can be clearly recognized in the photographic images before, during and after the landslide, and the change of position can be tracked. As can be seen from Figure 7, the mountain vegetation is distributed more evenly within 50 minutes before the landslide; around 50-90min in the landslide, the mountain vegetation shows a north-south spreading pattern; around 90-120min after the landslide, the mountain vegetation is collectively washed to a certain place in the mountain and concentrated due to the influence of debris flow and so on. And by utilizing the UAV tilt camera image multi-view fusion technology, tracking and monitoring technology, improved DeeplabV3+ network and other comprehensive processing of images, we can accurately fuse the positional changes of the mountain vegetation before, during and after the landslide in the civil engineering disaster motion monitoring system, and obtain a complete and coherent intuitive change of the mountain vegetation affected in Fig. 8.andr processing of images

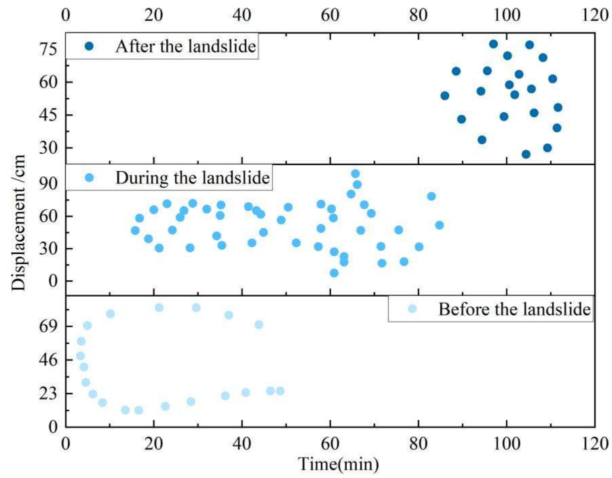

Figure 7: Images of mountain vegetation before, during and after the landslide

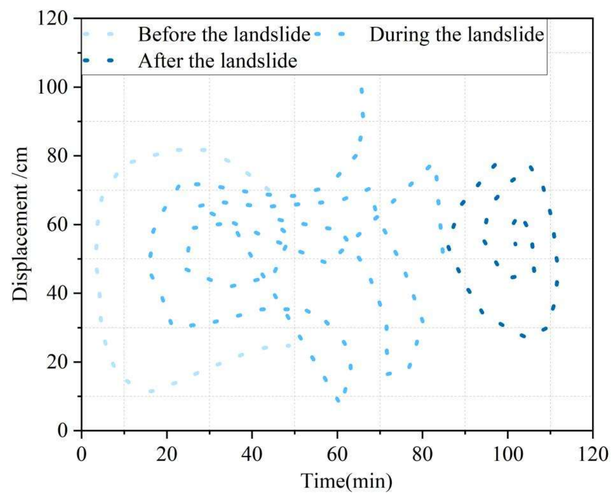

Figure 8: Mountain vegetation after multi-perspective fusion

III. B. 2) Comparison of image processing accuracy of different methods

The accuracy of different methods in processing civil engineering disaster photographic images is compared to verify the processing advantages of the integrated methods in this paper. The difference calculation method based on improved soil-adjusted vegetation index (MSAVI difference method), the iterative algorithm using minimum cut (FMIFSC method), and the climate data analysis method (CDAT method) are selected as the comparison methods to conduct the comparison experiments on noise removal and image fusion of multiple types of objects in civil engineering landslide disasters. Table 1 shows the comparison results of the processing accuracy of different methods. The image processing accuracies of the five types of civil engineering related objects of the integrated processing methods in this paper are 86.57%, 88.54%, 92.32%, 88.46%, and 89.75%, respectively. The highest image processing accuracy of the three comparison methods is only 58.77%, which is much lower than that of this paper's method. Therefore, it can be judged that the method of this paper has the best processing capability for UAV tilt photography images, and can accurately recognize and process the images obtained from civil engineering-related disaster monitoring.

Table 1: Comparison of processing accuracy of different methods

	MSAVI	FMIFSC	CDAT	Ours
Hillsides and gullies	39.47%	42.56%	55.50%	86.57%
Mountain vegetation	47.95%	44.64%	43.51%	88.54%
River channel	40.86%	45.10%	47.89%	92.32%
Infrastructure	58.77%	50.51%	50.13%	88.46%
Crops	55.61%	49.76%	50.16%	89.75%

III. C. Implementation and evaluation of the effectiveness of the drone monitoring program

After verifying the effectiveness of the image-processing technology, the technicians formulated a drone flight plan that included parameters such as flight altitude, speed and route, and ensured that the drone efficiently accomplished the monitoring task of inclined photography based on the topographical characteristics of the monitoring area and the historical record of landslide disasters. Equipped with a high-resolution camera and LIDAR, the drone operates along the predetermined flight route, acquiring real-time surface images and three-dimensional terrain data. With these data, technicians can identify potential hazardous points of landslides, such as surface cracks and rock displacement. The drone is also equipped with an infrared thermal camera for monitoring changes in surface temperature to help identify factors that may cause landslides, such as surface seepage. The collected data was transmitted in real time to the ground control station, where the technicians combined geological principles and used techniques such as image processing and pattern recognition to analyze the data in depth, and ultimately identify a number of potential landslide locations.

Table 2 shows the monitoring effect after UAV tilt camera image processing in the monitoring of landslide potential sites in Linzhi region of Tibet. Several key indicators have been significantly improved. The monitoring effectiveness was increased from 2 times per quarter to 4 times per quarter, which greatly improved the monitoring frequency and timeliness. The identification rate of potential danger points increased from 50% to 98%, an improvement of 48%, showing that the UAV tilt camera image processing technology is more accurate in the identification of landslide potential danger points. Early warning time was advanced by an average of 8 days, providing a valuable window of time for disaster prevention and control through timely monitoring and analysis. The economic loss was reduced by 1.6 million yuan from the original 2 million yuan to 400,000 yuan per year, effectively reducing the economic burden of local residents caused by landslide disasters.

Table 2: Implementation effect

Evaluation indicators	Before implementation	After implementation	Improvement
Monitoring efficiency	Twice per quarter	Four times per quarter	Three times per quarter
Identification rate of potential hazard points	50%	98%	48%
Lead time for early warning	1 day	9 days	8 days
Decreased economic losses	2000000 yuan per year	400000 yuan per year	1600000 yuan per year

IV. Conclusion

In this paper, we propose a UAV tilt-shot image processing technique that integrates multi-view fusion, error optimization and improved deep learning to validate its role in civil engineering landslide disaster monitoring. In this paper, the maximum error of 3D surface morphology between UAV tilted photography images and actual sensor images is only 7 mm. the image processing accuracy of five types of civil engineering disaster-related objects reaches up to 92.32%, which is higher than that of three types of comparative methods. The identification rate of hidden danger points is increased by 48%. Early warning time is advanced by 8 days. In the future, we can continue to optimize the stability of the model's image recognition processing under complex lighting conditions to improve the accuracy of disaster monitoring.

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