Application of unmanned aerial vehicle remote sensing technology in hydrological monitoring for water conservancy projects

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Abstract

The article provides a brief introduction to hydrological monitoring and the methods of water body identification and flow velocity estimation based on unmanned aerial vehicle (UAV) remote sensing technology. Then, a case study of hydrological monitoring using UAV remote sensing technology was conducted on Gangnan Reservoir in Hebei Province. The effectiveness of the convolutional neural network (CNN) algorithm was verified, and measurements were made on the reservoir's water area and average flow velocity in both flood and non-flood periods during 2020, 2021, and 2022. It was found that the CNN algorithm effectively identified water areas in UAV remote sensing images. Compared to non-flood periods, there was a significant increase in the water area of the reservoir during flood periods, as well as a noticeable increase in average flow velocity upstream; however, there was no significant change in average flow velocity downstream of the reservoir.

Keywords: unmanned aerial vehicle, remote sensing, water conservancy project, hydrological monitoring.

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Introduction

Unmanned aerial vehicles (UAV) are a result of technological advancement. Unlike traditional flying vehicles, UAV do not require direct human contact for piloting. Instead, they can be remotely controlled through wireless communication technology [1] or autonomously fly based on pre-set flight programs. Equipped with optical sensing equipment, UAVs are effective monitoring devices in various fields. In the domain of water conservancy projects [2], local hydrological monitoring plays a critical role in assessing water resources, mitigating flood disasters, and optimizing water resource allocation. Traditional hydrological monitoring methods are often influenced by factors such as terrain and environmental conditions. However, UAV remote sensing technology, being a novel hydrological monitoring approach, effectively overcomes these limitations by leveraging the UAV's inherent flexibility and efficiency [3]. Andriambeloson et al. [4] proposed a practical method for reconstructing historical and current flow and water depth time series using remote sensing and freely available datasets, combined with hydrological modeling, to facilitate operational monitoring of small ungauged watersheds. Pan and Khabazi [5] introduced a monitoring method based on remote sensing and geographic information system (GIS) for tracking the evolution of hydrological features in small watersheds. Experimental results indicated that this approach exhibited strong edge preservation, good noise reduction, and high monitoring accuracy. Furthermore, Zhang et al. [6] analyzed land use/land cover changes in Dongguan City of the Pearl River Delta metropolitan area since 1979 and their impact on urban runoff. The results revealed that the increase in annual surface runoff was closely related to urbanization and the central area of the city experienced the highest increase. This paper provides an introduction to water conservancy projects and hydrological monitoring, along with a description of the method employed for water body identification and flow velocity assessment utilizing UAV remote sensing technology. Subsequently, a case analysis of hydrological monitoring using UAV remote sensing technology was conducted on Gangnan Reservoir in Hebei Province.

Hydrological monitoring

Hydrological monitoring involves systematic observations of various physical, chemical, and biological characteristics of water bodies to obtain information on the quantity, quality, distribution, and changes in water resources [7]. Essential data such as water level, flow, and water quality are monitored, which are crucial for water resource statistics, planning, protection, and utilization. In the context of water conservancy projects, the construction of diverse engineering facilities does not mark their completion. Both pre and post-construction hydrological monitoring are equally significant [8]. Before the implementation of water conservancy projects, hydrological monitoring data serves as a reference for engineering design. Following the completion of such projects, continuous hydrological monitoring is necessary to comprehend their impact on the local water environment. This facilitates the timely detection and resolution of any issues arising from the water conservancy projects. Furthermore, this monitoring serves the dual purpose of safeguarding the safety and benefits of water conservancy projects while also protecting the local water environment [9].

Water body identification and flow velocity determination based on UAV

Traditional hydrological monitoring methods rely on field investigations carried out by monitors within the monitoring area. However, these methods are not only inefficient but also limited by terrain and environmental constraints, making it challenging to cover the entire investigation area thoroughly. With advancements in science and technology, there has been significant progress in hydrological monitoring equipment. Among these advancements, UAV remote sensing technology has emerged as a commonly used monitoring approach [10]. By utilizing UAVs as flight platforms equipped with various sensors and equipment, efficient, rapid, and accurate acquisition and processing of information from ground or water surface targets can be achieved. This article mainly uses UAV remote sensing technology to identify water bodies within the water conservancy project area and assess their flow velocities, in order to analyze the impact of water conservancy project on the local water environment.

When using UAV remote sensing technology to collect data from the area surrounding the water conservancy project, not only is image information related to water bodies collected, but also land image information in the vicinity [11]. Therefore, before further analyzing the hydrological information, the initial step involves identifying water bodies from the UAV-collected remote sensing imagery and extracting their respective areas. This process essentially addresses the challenge of image recognition by categorizing pixels in the UAV remote sensing images. Commonly employed methods include the water body index method and cluster analysis method. The former calculates a water body index based on the bands present in the remotely sensed image and uses this index to determine whether a pixel corresponds to a water body. The latter employs a clustering algorithm to classify pixels, thereby determining the spatial distribution of water bodies. However, due to the varied information contained within remote sensing images, both methods struggle to uncover deeper patterns, resulting in suboptimal classification outcomes. To address this issue, this paper employs the convolutional neural network (CNN) [12], a deep learning algorithm, to accurately identify water body regions in the UAV remote sensing images. The basic steps involved in this approach are as follows.

① The UAV remote sensing images are preprocessed by graying, filtering, and noise reduction.

② The preprocessed image is input into the input layer of the CNN, and then the CNN performs convolutional feature extraction on the image in the convolutional layer with the following formula:

$$x_j^l = f\left(\sum_{j \in M} x_i^{l-1} \cdot W_{ij}^l + b_j^l\right), \qquad (1)$$

where x_j^l is the convolutional output feature map, x_i^{l-1} is the feature output of the i-th convolutional kernel in the previous convolutional layer after pooling, W_{ij}^l is the weight parameter between the i-th convolutional kernel and the j-th convolutional kernel, b_j^l is the bias of j convolutional kernels in l layers, M is the number of convolutional kernels, and $f(\bullet)$ is the activation function.

③ The convolutional features are input into the pooling layer for compression. A specific pooling box slides over the convolutional features. Each slide compresses features within the pooling box. Depending on the requirements, the compression can be achieved through mean pooling or maximum pooling [13].

④ The number of convolution and pooling steps mentioned above will be determined based on the requirements, considering factors such as recognition accuracy and computational complexity. Subsequently, the compressed convolutional features will be fed into the output layer, and the softmax function will be utilized to generate the water body judgment result.

By employing the aforementioned CNN approach, the water bodies in UAV remote sensing images can be accurately identified to obtain information about the distribution patterns of the water bodies. By considering the scale of the remote sensing image, we can further determine the specific area covered by the water bodies.

Besides determining the distribution area of a water body, measuring its flow velocity is also crucial for hydrological analysis. In this study, the surface flow velocity of water bodies was measured by combining UAV remote sensing images with the particle image velocimetry (PIV) method [14]. The process is as follows.

① Tracer buoys are deployed within the targeted area of the water body.

② The UAV hovers over the designated area, continuously capturing remote-sensing images using an image sensor.

③ CNNs are employed to identify both the scope of the water body within the designated area and the tracer buoys on its surface.

④ The continuous images are extracted in chronological order at specific frame intervals. By comparing the flow direction and displacement of the tracer particles on the water surface, the flow velocity on the surface of the water body is calculated by combining the frame intervals.

Case study

1. Overview of the study area

This paper focuses on the application of UAV remote sensing technology for hydrological monitoring, using Gangnan Reservoir in Hebei Province as a case. Gangnan Reservoir plays a crucial role in flood control within the mountainous area of the Hutuo River. It is an important water management project in the region and its geographic location is depicted in Figure 1, with the reservoir marked by a red dot in the upper left corner. The control basin area of Gangnam Reservoir covers approximately 15,900 square kilometers, serving functions such as flood control, water supply, and irrigation. Through joint operation with Huangbizhuang Reservoir, the control basin area expanded to 23,400 square kilometers. The Hutuo River, where Gangnan Reservoir is situated, originates from Wutai Mountain in Shanxi Province. The basin under its control experiences a continental climate, characterized by significant variations in annual rainfall distribution. Over 80 % of the rainfall is concentrated during the flood season between June and September. The average annual temperature ranges from 4.1 to 12.9°C, while the average annual wind speed ranges from 1.7 to 9.0 m/s.

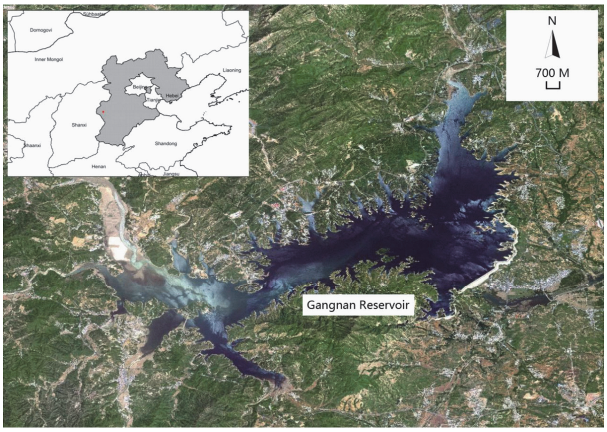

Fig. 1. Geographic location of Gangnan Reservoir

2. Test items

In the hydrological monitoring of the hydraulic engineering, UAVs were employed to collect remote sensing images. The model of the UAVs was DJI Mini 4 Pro (Shenzhen Dajiang Innovation Technology Co., Ltd.. China). When collecting remote sensing images, the UAVs flew according to a predetermined route and used their equipped camera to capture images of water areas around the reservoir. A total of 1,500 images with the same specifications and size were taken, and 1,000 of them were used as training samples and the remaining 500 were as test samples. Water and non-water areas in the images from both the training set and the test set were manually annotated.

Item 1: Testing the performance of CNN for water body recognition in UAV remote sensing images

A CNN was employed to accurately identify water bodies within UAV remote sensing images. The accurate recognition of water bodies is crucial for precise measurements of water area and flow velocity. To ensure the accuracy of these subsequent measurements, the performance of the CNN in water body recognition was first validated.

For training and testing the CNN, remote-sensing image samples were acquired using UAV technology. These images were manually labeled to distinguish between water-body and non-water-body regions. The CNN architecture was configured with two layers each for the convolutional and pooling layers. In the convolutional layer, 32 convolution kernels with a size of 3×3 were employed, while the pooling layer utilized a pooling frame of 3×3. The activation function used was the rectified linear unit (ReLU), and the stochastic gradient descent method [15] was utilized to adjust the parameters.

To validate the effectiveness of the CNN algorithms, this paper also conducted tests using the maximum interclass variance method (Otsu method) and the K-means clustering algorithm.

Item 2: Testing changes in the area of water within the reservoir during flood and non-flood periods

Between 2020 and 2022, remote sensing images were captured by UAV every other week during both the non-flood season (from February to April) and the flood season (from July to September) throughout the entire reservoir. The CNN algorithm was then employed to identify and extract the water areas within the remotely sensed images. Subsequently, the water area within the reservoir was calculated based on the scale of the remotely sensed images. The changes in water area during the flood season and non-flood season were compared, using the independent t-test for statistical analysis. A p value of less than 0.05 was considered statistically significant for detecting differences.

Item 3: Testing changes in mean flow velocity upstream and downstream of the reservoir during flood and non-flood periods

For the measurement of flow velocity in the reservoir, this study employed the white buoy tracking method. White buoys were released upstream and downstream, and their displacement was calculated by capturing images using the UAVs. The CNN algorithm was also used for tracer recognition. A total of 1,000 images was captured; 600 images were used for training and 400 images were used for testing to validate the performance of the CNN algorithm in recognizing tracers in the images.

During the non-flood season (February to April) and the flood season (July to September) of 2020, 2021, and 2022, white tracer buoys were deployed every other week at a distance of 1 km from the upstream inlet and downstream outlet of the reservoir. A UAV was used to capture continuous time-series images of the tracers, hovering above them. The displacement of the tracers over time was then utilized to calculate the flow velocities of the water body in the upstream and downstream reaches of the reservoir. The changes in the flow velocities during flood and non-flood periods were compared using independent t-tests. P values less than 0.05 indicate statistically significant differences.

3. Test results

The objective of the three water body recognition algorithms is to classify the water body region in UAV remote sensing images, making it a binary classification problem. To evaluate the performance of these algorithms, a confusion matrix was utilized. The recognition and segmentation results of the three algorithms for water and non-water areas are shown in Figure 2. It was seen that the CNN algorithm performed the best. Figure 3 presents a performance comparison of the three water body recognition algorithms. It is evident that the CNN algorithm outperformed the other two algorithms in recognizing the water body region. It achieved an accuracy of 98.9 %, a recall rate of 98.7%, and an F value of 98.8 %. These high-performance indicators indicated that the CNN algorithm could be used to measure the water area and determine the upstream and downstream flow velocities.

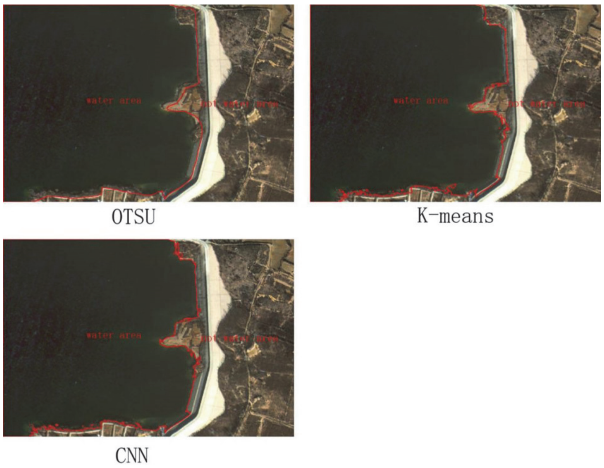

Fig. 2. The recognition results of the three algorithms

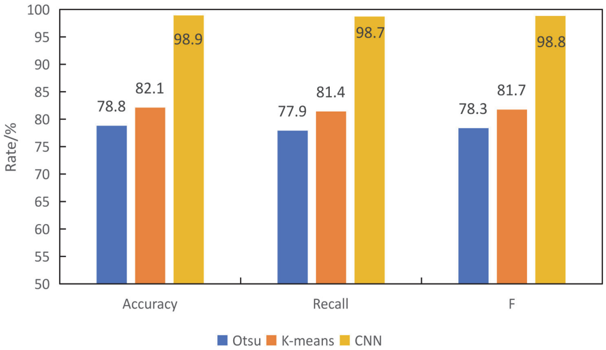

Fig. 3. Performance of three water body recognition algorithms

The remote sensing images of Gangnan Reservoir were acquired using UAV technology. After applying the CNN algorithm to extract the water body area, the calculations were performed to determine the water body area of Gangnam Reservoir during the flood season and non-flood season from 2020 to 2022, as presented in Table 1. It is evident that the water body area of Gangnam Reservoir during the flood season was significantly higher compared to the non-flood season within the same year. However, when comparing the water body area during the non-flood or flood periods across the years 2020, 2021, and 2022, there was no significant change observed.

The PIV method was utilized to measure the flow velocity in the upstream and downstream areas of the reservoir. Remote sensing images of the tracer buoys in the upstream and downstream regions were collected using UAV technology for the PIV analysis. The recognition performance of the CNN algorithm for the tracers is presented in Figure 4. The results of the PIV analysis are presented in Table 2. It is evident that each year, the average flow velocity upstream of the reservoir during the flood season was significantly higher compared to the non-flood season. However, there was no significant difference observed in the average flow velocity downstream of the reservoir between the two time periods.

Tab. 1. Water area of Gangnan Reservoir in flood and non-flood seasons from 2020 to 2022

Year	Non-flood season/$\times 10^4$ km	Flood season/$\times 10^4$ km	P value
2020	1.24 ± 0.21	1.63 ± 0.32	0.02
2021	1.23 ± 0.22	1.62 ± 0.33	0.01
2022	1.25 ± 0.23	1.64 ± 0.31	0.01

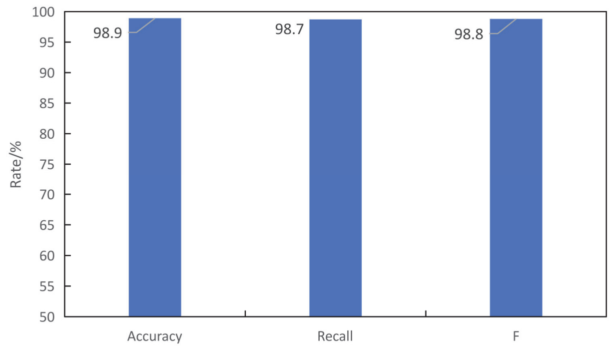

Fig. 4. The recognition performance of the CNN algorithm for the tracers

Tab. 2. Upstream and downstream flow velocities in Gangnan Reservoir during flood and non-flood periods from 2020 to 2022

Year	Test area	Non-flood season m / s	Food season m / s	P value
2020	Upstream of the reservoir	1.26 ± 0.36	2.36 ± 0.54	0.02
	Downstream of the reservoir	1.21 ± 0.32	1.22 ± 0.29	0.13
2021	Upstream of the reservoir	1.25 ± 0.29	2.35 ± 0.49	0.01
	Downstream of the reservoir	1.22 ± 0.31	1.21 ± 0.28	0.11
2022	Upstream of the reservoir	1.26 ± 0.32	2.36 ± 0.51	0.01
	Downstream of the reservoir	1.23 ± 0.28	1.22 ± 0.27	0.13

Discussion

Water conservancy projects encompass various activities aimed at managing and protecting water resources, preventing and controlling water-related disasters, and facilitating sustainable water resource utilization. Reservoirs are a type of water conservancy project that uses structures such as dams, embankments, sluice gates, and weirs to create artificial bodies of water in river basins. These reservoirs regulate runoff to reasonably distribute natural water resources. Even after the construction, water conservancy projects require monitoring and maintenance. Hydrological monitoring is crucial in this process and involves tracking parameters such as water levels, flow, water quality, and water temperature. Continuous hydrological monitoring helps in understanding the influence of water conservancy projects on water resources. UAV remote sensing technology has emerged as a valuable tool in hydrological monitoring. Compared to traditional monitoring methods, UAVs have advantages in terms of flexibility and efficiency in collecting information on surface waters.

This paper provides a case study of hydrological monitoring for Gangnan Reservoir in Hebei Province using UAV remote sensing technology. Firstly, the performance of the CNN algorithm for water body identification in remote sensing images was tested. Then, UAV remote sensing technology was employed to measure the reservoir's water area during both flood and non-flood periods in 2020, 2021, and 2022. Moreover, the flow velocity of upstream and downstream areas of the reservoir was measured using PIV. The final results are as described above. The CNN algorithm was capable of effectively identifying water areas in UAV remote sensing images. Compared to non-flood periods, the water area of the reservoir significantly increased during flood seasons, and the average flow velocity upstream also showed a significant increase. However, there was no significant change in the average flow velocity downstream of the reservoir. The reasons were analyzed. During the flood season, local rainfall increased, leading to an increase in surface runoff and a rise in average flow velocity upstream of the reservoir. As a result, the water storage capacity within the reservoir increased along with an expansion of its watershed area. The reservoir itself served as a buffer by storing water and could autonomously control discharge through opening gates, thereby regulating downstream flow velocity. Therefore, the average flow velocity downstream remained stable, further demonstrating the effectiveness of reservoir storage and buffering capabilities.

Conclusion

This paper briefly introduces hydrological monitoring and the utilization of UAV remote sensing technology for water body identification and flow velocity assessment. Gangnam Reservoir in Hebei Province was taken for a case study of hydrological monitoring under UAV remote sensing technology. The performance of the CNN algorithm in identifying water body areas in remotely sensed images was evaluated. Subsequently, the water body areas of the reservoir during flood season and non-flood season in the years 2020, 2021, and 2022 were measured using UAV remote sensing technology. Moreover, the flow velocities in the upstream and downstream areas of the reservoir were measured using the PIV method. The findings are as follows. (1) The CNN algorithm demonstrated effective recognition of water body areas in remotely sensed images, making it suitable for subsequent measurements. (2) The water area of Gangnan Reservoir exhibited a significant increase during the flood season compared to the non-flood season within the same year. (3) In each year, the average flow velocity upstream of the reservoir was significantly higher during the flood season than during the non-flood season. However, there was no significant difference in the average flow velocity downstream of the reservoir between the two time periods.

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