Video Characteristics and Intelligent Recognition Methods for Water Inrush in Wangjiazhai Tunnel, Yunnan: Postprint

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Abstract

Taking the water inrush in the semi-lithified tunnel of Wangjiazhai, Yunnan as the engineering background, this study analyzes the video characteristics throughout the entire water inrush process, selects a deep learning model suitable for identifying tunnel water inrush features, and utilizes the Mask R-CNN network to achieve classification and segmentation of water inrush in the Wangjiazhai semi-lithified tunnel. The main research contents completed are as follows: (1) Analyze the causes of water inrush disasters in the Wangjiazhai tunnel and summarize the treatment measures for water inrush sections: respectively adopt comprehensive dewatering to reduce the confined water head on the tunnel face, in-tunnel curtain grouting, and dense pipe roofing and small pipes to increase the bearing capacity of the arch, ensuring stability during excavation and construction safety. (2) Analyze on-site video images of the Wangjiazhai tunnel to obtain basic video characteristics of water inrush: 1) The suddenness of the disaster; 2) The scale of water inrush; 3) High sediment content in water inrush; 4) Both suddenness and precursory signs, and simultaneously propose a classification method for water inrush levels. (3) Create a typical image dataset of water inrush in the Wangjiazhai tunnel, Yunnan, utilize the Mask R-CNN network for training and learning on samples, and achieve intelligent classification and segmentation of different types of water inrush. The mAP of the test set reaches 90.0%, and compared with Faster R-CNN, Mask R-CNN demonstrates stronger capability in extracting and expressing water inrush features of the Wangjiazhai tunnel, while simultaneously exhibiting higher accuracy.

Full Text

Research on Intelligent Recognition and Characteristic Analysis of Water and Mud Bursting in Wangjiazhai Tunnel

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Abstract

Taking the water-mud bursting disaster in the Wangjiazhai semi-diagenetic tunnel as the engineering background, this study analyzes the video characteristics throughout the entire process of bursting occurrence and employs a deep learning model suitable for recognizing tunnel bursting features. Using the Mask R-CNN network, we achieve classification and segmentation of water-mud bursting events in the Wangjiazhai semi-diagenetic tunnel. The main research contents are as follows: (1) We analyze the causes of water-mud bursting disasters in Wangjiazhai Tunnel and summarize treatment measures for bursting sections, including comprehensive dewatering to reduce confined water head at the tunnel face, in-tunnel curtain grouting, densely arranged pipe sheds, and small advance pipes to increase the bearing capacity of the arch, ensuring stability and construction safety during excavation. (2) We analyze on-site video images from Wangjiazhai Tunnel to obtain basic video characteristics of bursting: 1) the suddenness of disasters; 2) the scale of bursting; 3) high sediment content in the burst material; and 4) both suddenness and predictability. Simultaneously, we propose a classification method for bursting severity levels. (3) We create a typical image dataset of water-mud bursting in Wangjiazhai Tunnel and utilize the Mask R-CNN network for training and learning, achieving intelligent classification and segmentation of different types of bursting. The test set achieves a partial mAP of 90.0%, demonstrating that Mask R-CNN possesses stronger feature extraction and representation capabilities for Wangjiazhai Tunnel bursting characteristics compared to Faster R-CNN, while also achieving higher accuracy.

Keywords: mountain tunnel; deep learning; rating of water and mud bursting; video characteristics; semantic segmentation

1. Introduction

Since the 21st century, with the continuous deepening of the "Western Development" and "Belt and Road" initiatives, China's investment in western region construction has continuously increased, leading to the construction of numerous highway and railway tunnel projects in western areas. Tunnel projects in western mountainous regions typically face complex geological conditions, long construction periods, high construction difficulty, and numerous uncertain factors, often resulting in various geological disasters during construction. Common tunnel construction geological disasters include large deformation, ground subsidence, collapse, mud bursting, water inrush, and roof falling. Among these, tunnel water-mud bursting represents a typical geological disaster that frequently occurs in numerous mountain tunnel constructions [1~2].

Currently, the detection of water-mud bursting accidents relies primarily on manual methods. However, due to individual factors, limited space, restricted vision, and difficult sound wave transmission in tunnel environments, disasters are often difficult to detect promptly, frequently leading to significant casualties. When disasters occur, workers' lives are threatened, and their instinctive reaction is to flee the dangerous area, making it difficult to report accidents in a timely and effective manner. Therefore, developing intelligent recognition and monitoring technology for water-mud bursting disasters is critically important.

In recent years, artificial intelligence technology has gained widespread attention for water-mud bursting recognition in tunnels [3]. Zhang Wangjing et al. [4] combined neural network models to propose a coal mine water disaster prediction system, providing an effective means for identifying water inrush accidents in mines. Yang Zhuo and Ma Chao [5] selected six primary factors including groundwater level and rock stratum dip angle as evaluation indicators, using BP neural network methods to assess and identify water-mud bursting risks in karst tunnels. Bai Chenghao [6] analyzed disaster-causing factors of different types of tunnel water bursting and developed an intelligent prediction system for karst tunnel water-mud bursting based on machine learning. Cao Yuchao [7] proposed a low-resolution water inrush recognition method based on superpixels and texture features, utilizing texture features for water-mud bursting identification and solving the problem of low-resolution water-mud bursting recognition.

Currently, intelligent analysis objects for tunnel water-mud bursting disaster monitoring and recognition primarily focus on structured data, with limited research on unstructured data such as surveillance video images. When water-mud bursting occurs, the time for sediment and water to inundate the working face or tunnel depends on factors such as water pressure, inflow volume, and flow velocity, ranging from several seconds to several minutes or even lasting for hours. It is essential to capture the engineering characteristics of bursting, identify it promptly, and implement corresponding treatment and drainage measures while evacuating personnel to prevent accident escalation. Subsequently, intelligent recognition of water-mud bursting and timely information transmission are significant for enabling managers to make correct decisions promptly, thereby minimizing personnel and property losses.

2. Project Overview and Analysis

2.1 Project Overview

The Wangjiazhai Tunnel entrance is located in Linxiang District, Lincang City, while the exit is located in Shuangjiang Lahu, Wa, Bulang, and Dai Autonomous County. The right tunnel has a total length of 8,040 meters, with start and end stakes at K21+440~K29+480 and a maximum burial depth of approximately 1,022 meters. The left tunnel spans from ZK21+460 to ZK29+470, with a total length of 8,010 meters and a maximum burial depth of about 1,002 meters.

The left tunnel section ZK23+025~ZK22+874 passes through weakly weathered granite, situated in the alteration zone between Tertiary quartz sandstone, Tertiary quartz sandy conglomerate, and the transition zone, representing a contact zone between hard rock and soft-hard rock, and a strongly to moderately water-rich alteration zone with complex and variable hydrogeological conditions. The remaining unexcavated section has experienced multiple large-scale mud-water bursting incidents, forming extensive "remolded soil" geological conditions with disturbed and damaged stratum conditions. Since construction began in March 2018, over twenty large-scale water-mud bursting geological disasters have occurred, with more than ten causing roof collapse, significantly impacting construction progress with an average daily advance of less than one meter, posing prominent constraints on the overall tunnel schedule. The three adverse factors of "water-rich, high-pressure, and poor geology" have made construction difficulty and safety risks beyond imagination, with water-mud bursting prevention technology reaching unprecedented difficulty levels and attracting high attention from the engineering community.

2.2 Cause Analysis of Water-Mud Bursting in Wangjiazhai Tunnel

Based on statistical analysis of water-mud bursting cases in Wangjiazhai Tunnel, the causes are summarized as follows: (1) **Stratum lithology:** The surrounding rock at the Linxiang end consists of Tertiary sandstone interbedded with claystone semi-diagenetic rock, characterized by poor cementation, extremely soft rock quality, large void ratio, high saturation, cracking upon water loss, easy softening upon water exposure, and susceptibility to "paste-like" bursting (outburst) when disturbed. Meanwhile, the tunnel face is prone to piping disasters that entrain sandy particles, hollowing out the stratum and developing into large-scale mud-water bursting disasters. (2) **Surface water and groundwater:** Due to geological structure, the sandstone layer has high porosity, low density, and good water-bearing capacity. The stratum water is strongly water-rich with high water head, showing obvious "water pocket" distribution characteristics. The groundwater content in the sandstone layer is nearly saturated, and the sandstone and clay layers soften and lose strength, making mud-water bursting geological disasters highly likely. (3) **Structural design:** Wangjiazhai Tunnel employs reverse slope construction, which largely causes water flowing back above the tunnel face and infiltrating water to continuously accumulate.

As the water level gradually rises, water pressure will continuously increase, destroying the stability of the rock mass itself and continuously increasing the overlying soil pressure. (4) **Surface collapse and roof falling:** The surrounding rock has extremely poor self-stability, making it difficult to form a caving arch effect, rendering the "fully utilizing surrounding rock self-stability capability" concept in the New Austrian Tunneling Method inapplicable. Therefore, when mud-water bursting disasters occur, they often cause surface roof falling.

2.3 Analysis of Water-Mud Bursting Prevention Measures in Wangjiazhai Tunnel

Based on the cause analysis above, prevention measures for Wangjiazhai Tunnel are summarized as follows: (1) **Comprehensive dewatering:** To reduce water pressure above the tunnel face and control bursting risks, dewatering and drainage are required to reduce confined water head. However, single dewatering schemes are difficult to achieve expected effects due to factors such as large water volume per unit area, small influence range, and long time required for dewatering to reach excavatable conditions. Therefore, a comprehensive dewatering scheme is adopted, combining surface deep well dewatering as the main method, supplemented by in-tunnel well point dewatering, advance drilling drainage at the tunnel face, and pipe-jacking advance pilot tunnel drainage, integrating drainage and blocking to ensure construction safety and schedule requirements. (2) **In-tunnel curtain grouting:** To reinforce and improve soil mass, block water seepage, improve excavation conditions, and prevent hole collapse and drilling failure during pipe shed construction, advance curtain grouting is implemented before pipe shed installation. Using a drilling-grouting integrated machine, two rings of advance grouting holes are drilled at 40 cm and 80 cm positions within the upper bench excavation contour line, with grouting pressure controlled at 3-4 MPa. Grouting materials include cement slurry and cement-sodium silicate double slurry. Only after achieving the expected reinforcement effect from in-tunnel curtain grouting can dense pipe sheds be installed, as shown in Figure 2 [Figure 2: see original paper]. (3) **Dense pipe shed:** To improve soil mass in the arch area and effectively form a reinforcement ring, Φ89 pipe sheds are installed on the upper bench after advance grouting, with a circumferential spacing of 25 cm and a length of 9-15 meters. During pipe shed installation, supplementary grouting is applied to weak grouting zones in front of the tunnel face based on drilling conditions. The dense pipe shed arrangement forms a row of pre-control shed protection, increasing the bearing capacity of the arch, ensuring stability during excavation and controlling initial support deformation, reducing the risk of sliding collapse and water-mud bursting while avoiding low efficiency, high cost, and uncontrollable risks associated with large-area curtain grouting reinforcement. (4) **Advance small pipes:** To control over-excavation and ensure construction safety, advance small pipes are intensified by adjusting their length and implementing support after each excavation section, with advance small pipes installed for each steel frame. This effectively reduces disturbance and falling blocks during milling excavation, ensuring excavation 成型 and construction safety while reducing bursting risks. (5) **Rapid emergency measures:** When small-scale water-mud bursting occurs locally, to prevent deterioration, timely closure is required using reinforced stone cages to block water flow, supplemented by precise local grouting to compact and densify the surrounding rock within the bursting range.

3. Video Characteristics and Classification

3.1 Video Characteristic Analysis of Water-Mud Bursting in Wangjiazhai Tunnel

Unlike typical mountain karst tunnel water inrush, water-mud bursting in Wangjiazhai Tunnel often presents as droplet, shower, or flow patterns during excavation, which may develop into large-scale sudden bursting hazards when passing through certain sections. Based on site investigation and monitoring of on-site surveillance videos, the typical bursting characteristics of Wangjiazhai Tunnel are summarized as follows: (1) **Suddenness of bursting:** The sudden collapse of the tunnel face is one of the prominent features of water-mud bursting in Wangjiazhai Tunnel. The suddenness of face collapse, significantly different from ordinary surrounding rock failure, is directly caused by the instantaneous failure of water-blocking measures such as horizontal jet grouting piles when the tunnel face is excavated and settlement control is lost. The high water pressure and soil pressure accumulated in the mountain cause mud-water to gush out, generating strong water wave vibrations that lead to frequent changes in surface ripple characteristics. (2) **Scale of disasters:** Water-mud bursting in Wangjiazhai Tunnel exhibits considerable scale. When disasters occur, large water flows rush into the tunnel interior, creating dramatic changes in flow velocity and volume, with complex and violent changes in macroscopic morphological characteristics of the affected areas—representing one of the primary video features of bursting events. (3) **High sediment content:** Large-scale water-mud bursting in Wangjiazhai Tunnel often carries substantial amounts of sediment. Water flow containing more sediment typically appears more turbid, with color characteristics different from clear water, turning gray-brown or light brown. (4) **Both suddenness and predictability:** Once water-mud bursting deteriorates in Wangjiazhai Tunnel, its scale is often large and development rapid, yet it simultaneously exhibits certain predictability. Before deterioration, initial support settlement increases dramatically, cracking and deformation occur, water outflow volume in the tunnel suddenly increases, and sediment content at water outlets increases. Detecting color changes in videos can reflect changes in sediment content, thereby judging the severity of bursting events. (5) **Often triggers roof falling and surface collapse:** Since construction began, among the 16 large-scale water-mud bursting geological disasters occurring over five years, 10 caused roof falling and surface collapse. For instance, on June 2, 2018, the left tunnel face at ZK21+554 at the Linxiang end of Wangjiazhai Tunnel collapsed with sediment outflow, causing roof collapse. On June 15, two collapses occurred, forming a surface pit 21 meters long, 22.5 meters wide, and 11 meters deep, with approximately 2,887 cubic meters of mud outburst.

In summary, water-mud bursting in Wangjiazhai Tunnel shares both similarities and distinct differences with typical water bursting: (1) Both exhibit characteristics of suddenness, scale, and mud-water mixture, showing video features such as frequent surface ripple changes and irregular complex macroscopic morphology, but Wangjiazhai Tunnel bursting emphasizes short-term sudden mud-water outburst. (2) Both possess certain predictability, but before Wangjiazhai Tunnel bursting deteriorates, it often shows increased sediment content leading to different color video features, whereas typical water bursting focuses more on changes in water inflow volume and flow velocity.

3.2 Classification of Water-Mud Bursting Severity in Wangjiazhai Tunnel

GB12329-90 *Karst Geology Terminology* defines "karst water inrush" as the sudden large-volume water outflow from groundwater stored and moving in karst aquifers when artificially exposed or affected by natural factors, often accompanied by sand and mud outflow. Classification by water volume changes includes concentrated inflow and constant inflow; classification by unit time inflow volume includes extra-large, large, and small inrush, as shown in Table 1 ; classification by gushing water volume divides karst water inrush into small gushing (<100 m^3/d), medium gushing (100~1000 m^3/d), large gushing (1000~10000 m^3/d), and extra-large gushing (>10000 m^3/d).

Current on-site response to water-mud bursting in Wangjiazhai Tunnel still faces many problems. When the impact on construction is not obvious, monitoring and treatment are typically not implemented. Only when significant impacts occur are mud-water bursting volumes monitored. The threshold requiring heightened vigilance and remedial measures from site personnel remains unclear. Based on practical engineering needs, we propose a classification method that better reflects disaster characteristics of typical water-mud bursting such as that in Yunnan's Wangjiazhai Tunnel. Based on on-site video image acquisition, Wangjiazhai bursting is divided into three levels, as shown in Table 2 .

Regarding sediment content, based on comparative analysis of different types of on-site monitoring videos, the characteristic features of each bursting level in Wangjiazhai Tunnel are summarized, as shown in Table 3 . How to intelligently identify and classify water-mud bursting disasters with low cost, high efficiency, and intelligence represents an important current challenge. With the development of deep learning, image recognition algorithms based on convolutional neural networks provide possibilities for solving this problem. While target detection algorithms can locate bursting occurrences, they cannot calculate parameter information such as coverage area; instance segmentation algorithms can segment all bursting locations but cannot distinguish bursting categories. Therefore, this paper proposes a bursting classification and segmentation method based on the Mask R-CNN [8] model, which not only classifies different severity levels of bursting but also completes segmentation of different levels.

4. Methodology and Results

4.1 Data Preparation

The dataset for this study was obtained through on-site camera video recording. To prevent high similarity between adjacent frames, images were extracted every 4 frames to form the dataset. High-quality images were manually selected, and typical bursting samples were classified by severity level. Due to limited bursting videos, only 150 samples were generated after selecting high-quality images. To enrich the dataset and further improve recognition efficiency, this study utilized the OpenCV open-source library to expand the dataset through data augmentation, thereby enhancing model generalization capability and preventing overfitting. After processing, the water-mud bursting sample dataset used for training and testing contained 960 images, with 720 used for training and 240 for testing. Each image was under 2 MB in size. After processing the water-mud bursting image data, LabelMe software was used to annotate bursting locations in dataset images. The annotation labels used in this study were mud1, mud2, and mud3, representing high-risk, medium-risk, and low-risk bursting, respectively. Partial annotated images are shown in Figure 4 [Figure 4: see original paper].

4.2 Bursting Level Recognition

Figure 5 [Figure 5: see original paper] shows the recognition results for these three bursting levels. The results demonstrate that Mask R-CNN performs well in bursting classification, successfully identifying the defined severity levels. However, the model's segmentation of bursting contours is not entirely accurate in some areas, possibly because when bursting contains high sediment content, target features are similar to tunnel environment features. The visualization after model segmentation is satisfactory. For video images with good recognition results, this study utilized the OpenCV open-source library to extract specified colors from the segmented bursting images, obtaining the bursting range in the images. By finding contours and calculating their area, the coverage area of the bursting portion was obtained.

4.3 Recognition Accuracy Analysis

The Precision-Recall curve (PR curve) effectively addresses the limitation of single-threshold performance evaluation by setting a series of different thresholds to provide different classification results, demonstrating the overall performance of the classifier and allowing selection of appropriate classification thresholds based on specific requirements, making it more practical in real scenarios.

Average Precision (AP) represents the area under the PR curve, calculated through integration. Generally, larger AP values indicate better detection performance for that category. Mean Average Precision (mAP) represents global model performance, being the mean of AP values across all categories.

This study used ResNet101 as the feature extraction network for model training and testing. Figure 6 [Figure 6: see original paper] shows PR curves for Mask R-CNN and Faster R-CNN [9] recognition of different bursting types on the test set, where the area under the PR curve represents recognition effectiveness for each category. Comparing Mask R-CNN with Faster R-CNN, Table 4 presents comparison results under several evaluation metrics. The charts show that Mask R-CNN achieves a test set mAP of 90.0%, demonstrating higher overall accuracy compared to Faster R-CNN, reflecting stronger feature extraction and representation capabilities for bursting characteristics. In terms of recognition effectiveness, it performs better on medium-risk and high-risk bursting, while low-risk bursting recognition is relatively weaker. Similarly, Faster R-CNN also shows unsatisfactory performance on low-risk bursting recognition.

4.4 Bursting Development Analysis

This study selected typical bursting development video images from the samples. Since bursting occurs on the tunnel floor and assuming constant bursting channel depth, the bursting coverage area can reflect changes in bursting flow to some extent. By selecting representative moments—A, B, C, and D representing the start, development, maximum scale, and recession moments, respectively, as shown in Figure 7 [Figure 7: see original paper]—and plotting time on the horizontal axis and the rate of area change at each moment relative to the start moment on the vertical axis, the curve of area change rate over time was obtained, as shown in Figure 8 [Figure 8: see original paper].

The curve shows that before bursting deterioration, the area growth rate is relatively slow over time. At approximately 15 seconds in the video, bursting begins to develop rapidly, reaching 60% of maximum scale within 5 seconds. Around 30 seconds, bursting scale reaches its maximum, then gradually decreases, though coverage area remains larger than at the start. This curve demonstrates the disaster characteristics of Wangjiazhai Tunnel bursting, with less than 5 seconds from initial deterioration to relatively complete development, fully reflecting the suddenness of bursting while providing reference for subsequent flow measurement.

5. Conclusions

Based on the Wangjiazhai Tunnel project in Yunnan and combined with water-mud bursting cases occurring during tunnel construction, this study aimed to utilize artificial intelligence methods for bursting recognition, yielding the following conclusions: (1) By analyzing the causes of water-mud bursting disasters, we summarized treatment schemes for tunnel bursting sections: comprehensive dewatering to reduce confined water head at the tunnel face; in-tunnel curtain grouting, dense pipe sheds, and small advance pipes to increase arch bearing capacity, ensuring stability during excavation and construction safety. (2) Using on-site video images, we analyzed water-mud bursting in Wangjiazhai Tunnel and summarized its video characteristics: 1) Disaster suddenness: frequent changes in surface ripple characteristics; 2) Bursting scale: complex changes in macroscopic morphological features; 3) High sediment content: color characteristics appearing gray-brown or light brown; and 4) Both suddenness and predictability. Based on practical engineering needs and combined with disaster characteristics of Wangjiazhai Tunnel bursting, we propose a severity level classification method. (3) We created a typical image dataset of water-mud bursting in Wangjiazhai Tunnel and utilized the Mask R-CNN network for training and learning, achieving classification and segmentation of different bursting types with a test set mAP of 90.0%. Finally, based on segmented images, we plotted the curve of bursting coverage area change rate over time, clearly reflecting the bursting characteristics of Wangjiazhai Tunnel.

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