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PDC bit wear detection based on YOLO v5 and OpenCV

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ABSTRACT: In recent years, due to the remarkable advantage of increasing speed and reducing cost, PDC bits has occupied a dominant position in the oil bits market. In the drilling process, the bit will wear itself when breaking hard rock. When the abrasion reaches a certain degree, the drilling efficiency of the bit will be significantly reduced. Therefore, during the drilling process, it is necessary to change the bit in time to ensure the rate of penetration. The wear degree of cutters is the key factor affecting the efficiency of PDC bit. In order to quantitatively monitor the wear degree of cutters, computer image recognition is adopted to judge the bit abrasion level by analyzing the missing proportion of each cutter. The data set is made from the bit data used in Sichuan, China. We locate the position of each cutter to get coordinates based on YOLO v5, a deep learning algorithm of object detection. Then, we use OpenCV cropping the whole image with those coordinates to acquire every picture of cutters and perform noise reduction and smoothing. After that, the processed cutter images are used to calculate the missing area, and use the proportion to confirm the wear degree.

Key words: PDC bit, Wear degree, Image recognition, YOLO v5, OpenCV

1. BACKGROUND

Nowadays, roller cone bits and PDC bits are the most commonly used bits in the field of oil drilling. With the continuous improvement of PDC bit cutter technology, PDC bit has become an important tool for drilling speed. Compared with traditional roller cone bits, PDC bits offer significant advantages in cost, rate of penetration and footage per bit when drilling formations, especially in deep and high-pressure wells.[1] Although PDC bits has high wear resistance, it's inevitable that the PDC bits being worn out. If the bit abrasion reaches a certain degree, the drilling efficiency of the bit will be significantly reduced. Therefore, it is necessary to obtain the wear condition of the drill bit in time to ensure the drilling speed.[2]

According to the wear characteristics of PDC bit, it can be divided into two kinds of wear: one is the normal wear, the cutter and rock produce continuous or intermittent friction, to break the rock. The process of the friction between the cutter and the rock produces micro-cutting, scratching, rubbing and so on to make the bit wear and blunt. The typical characteristics are continuous groove-like wear marks on the side and tooth column of the PCD layer where contacting with the formation, and the cracks in the grooves are extremely rare while the other PCD layers do not have delamination phenomenon. The other kind of wear is abnormal wear, such as tooth collapse, chip drop, polycrystalline diamond layer falls off.

PDC cutter failure directly leads to PDC bit failure. Once the bit fails, it will lose the drilling ability, resulting in stuck bit. This has a huge impact on the entire drilling work. Therefore, it is very important to judge the wear condition of the PDC cutting teeth quantitatively and reasonably and replace the drill bit in time.[3]

This paper mainly studies PDC bit abrasion under normal working conditions. In this paper, the current bit wear is judged by using YOLO v5 to locate the cutter position of the bit and using OpenCV to calculate the bit wear degree.

2. INTRODUCTION

2.1. *COMPUTER VISION*

Computer vision was born in "The Summer Vision Project" of MIT AI Group in 1966. It refers to use the computers to recognize and understand the content in images or videos. The core problem of the research is how to organize the input image information, divide the object and background, and then interpret the image content. After more than 50 years of development, computer vision has become an active research field. In the application of artificial intelligence, computer vision plays a key and irreplaceable role in detection, measurement, classification, positioning and other computer fields.

Since 2010, computer vision has exploded with the development of deep learning. The mainstream deep learning of computer vision is the convolutional neural network. It can learn image features layer by layer, which can be divided into low-level, such as edges and textures of images, and high-level features which is the combination of low-level features. Convolutional neural network simulates the hierarchical information processing mechanism of human brain so it can obtain image features directly from original pixels. Through deep neural network, the recognition accuracy of various vision-related tasks has been greatly improved. As a result, computer vision has begun to be implemented from scientific research to industrialization.[4]

2.2. *YOLO*

In 2015, Redmon J proposed the YOLO object detection algorithm, which solved the object detection as a regression problem. Through a one-stage neural network, YOLO completes the input from the original image to the output of object location and category with a speed of 45, realizing the real-time object detection. Based on the YOLO v1, Redmon proposed YOLO v2 and YOLO v3, which used partial Anchor mechanism, and changed the backbone to Darknet-53. In the coco dataset, YOLO v3 achieved the mAP of 57.9% in 51ms, compared with the Retina-Net whose achieved mAP of 57.5% in 198ms, but 2.9 times faster.[5]

In 2020, Aiming at the defects of YOLO v3, Ultralytics proposed YOLO v5. YOLO v5 has four parts, namely, the Input, Backbone, Neck, and Prediction. The Input is mainly used for image reading and preprocessing. YOLO v5 uses Mosaic data enhancement technology to improve the training speed and network accuracy of the model and proposes an adaptive anchor frame calculation and adaptive image scaling method. Backbone is a part of convolutional neural network part that aggregates and forms image features on different fine-grained images. It continues to use the CSP structure from YOLO v3 and adds the Focus structure. Neck is a series of network layers that mix and combine image features, and it pass them to the prediction layer. In YOLO v5, FPN and PAN structure are applied to the Neck layer. Prediction is to predict image features, generate bounding boxes and predict categories.

YOLO makes the real-time computer vision possible. The algorithms and software generated by YOLO are playing an important role in intelligent transportation, healthcare, industry, etc. Like vehicle detection, YOLO is used to identify, locate and classify vehicles in images or videos, and to detect and track the vehicles, capture their violations, and control the traffic.[6] Similarly, YOLO is applied to many modules in autonomous robotic cars or autonomous vehicles, such as positioning and mapping, scene understanding, motion planning, and driver status.[7]

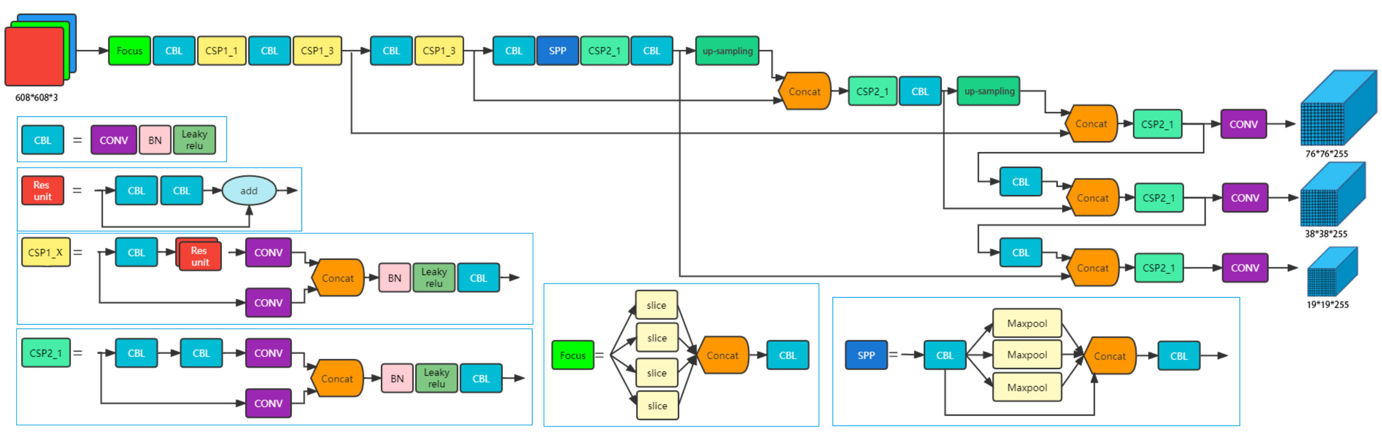

Fig. 1. The structure of YOLO v5, contains the Input, Backbone, Neck, and Prediction.

2.3. *OPENCV*

OpenCV is an open-source computer vision library, which provides basic computer vision functions from the most basic filtering to advanced object detection. It's also providing the machine learning module, which you can use KNN, SVM, Decision Tree, Random Forest, ANN and so on.

OpenCV has C++, Python, Java and MATLAB interfaces, and supports Windows, Linux, Android and Mac OS. OpenCV mainly tends to real-time visual applications. It is now also available for C#, Ch, Ruby, GO.

OpenCV-Python is the Python API for OpenCV, combining the best features of OpenCV, C++, API and Python. With OpenCV-Python, we can use Python to solve computer vision problems. In recent years, OpenCV has been widely used in petroleum engineering. For instance, with the development of the micro-computed tomography scanning technology, digital rock physics technologies came into possible with OpenCV. High-quality three-dimensional images of rock samples can be obtained by micro-computed tomography. Next, with the method based on OpenCV, we can divide the grayscale image into three reasonable components, including mineral, organic matrix, and pores, and use them to establish digital rock models.[8] Many of YOLO's applications rely on OpenCV, such as the Gaussian smoothing algorithm and the canny edge detector.[7]

3. EXPERIENCE

3.1. DATA SET AND THE ENVIRONMENT CONFIGURATION

The degree of wear of a PDC bit is largely determined by the counterpart of the PDC bit's cutters, which are located at the edge of each tooth and can be easily detected from the teeth itself.

In this experiment, we used pictures of different types of PDC bits from Sichuan, China. After screening and removing unqualified images, we collected 133 pictures of PDC bits of different types and used them as datasets. The images will be divided into training set, validation set and test set in an 8:1:1 ratio.

Object detection requires manual annotation on the sample data. After that, the model can acquire self-learning ability by learning the labeled sample features. In this paper, we use the online tool Make Sense to mark the positions of all cutters by drawing the boxes in each single tooth image of the training set and verification set. Finally, we obtained 93 cutters image data sets, and saved each data as an independent text file.

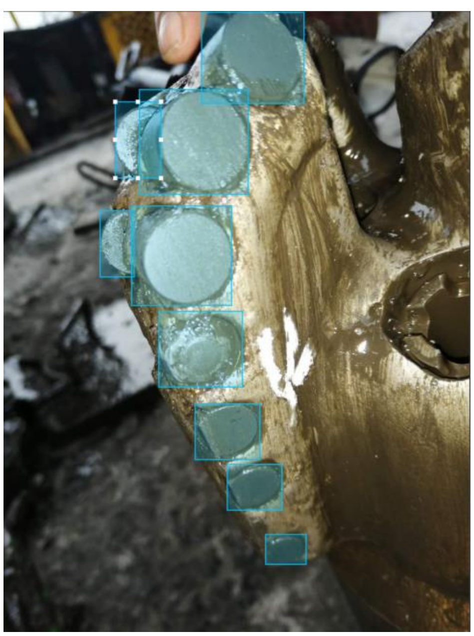

Fig. 2. The picture with drawing the cutter's position.

In this paper, the deep learning framework used in training YOLO v5 is Pytorch. Other environment configurations are as follows:

Table 1. Hardware Resource Configuration

Name	Version
OS	Window 10
CPU	Inter i7 7700K
GPU	GTX1080
RAM	32GB

Table 2. Software Resource Configuration

Name	Version
Python	Window 10
OpenCV-Python	Inter i7 7700K
Pytorch	1.10.2+cu102
Pycharm	2021.2.2
Anaconda3	4.10.1

3.2. MODEL TRAINING PROCESS AND EVALUATION

First, we saved the image which labeled by Make Sense and the corresponding text file of the image. Then, we divided the data set into training set and verification set. After setting the model parameters and paths, we trained through YOLO v5. The model optimizes the training process by constantly adjusting parameters. After 300 epochs, we obtained the PDC bit cutter object detection model.

The commonly used performance evaluation indexes in the field of object detection include accuracy, precision, confusion matrix, recall, average precision (AP), mean average precision (mAP), ROC+AUC, Precision-Recall curve (PR), etc.

P and N indicate that the predicted value is positive sample and negative sample respectively, while T and F indicate that the predicted value is the same or different from the real value.

Table 3. Confusion Matrix

Confusion Matrix		Predict	
		P	N
Real	T	Ture Positive, TP	False Negative, FN
	F	False Positive, FP	True Negative, TN

The precision represents the proportion of the positive sample in which the predicted value is correct. Precision is used to measure the accuracy of classifying positive samples by classifier, and the calculation expression is Eq. (1):

$$\boldsymbol{p} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \tag{1}$$

To evaluate the performance of a classifier, we should not only rely on the precision, but also need another evaluation index: Recall. Recall is the proportion of all positive samples predicted, measured by the ability of the classifier to predict positive samples correctly, and its calculation expression is Eq. (2):

$$\boldsymbol{R} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \tag{2}$$

Precision and Recall are often at odds with each other. In the training process, if the Precision can remain unchanged or increase, and the Recall can also improve, it indicates that the performance of the classifier has been improved. On the contrary, if only the Recall increases, the Precision decreases, then the performance of the classifier is poor. In general, we use PR curve to represent the balance between Precision and Recall of this classifier.

AP is equal to the area bounded by the Precision-Recall curve and the coordinate axes. In general, the area size is proportional to the performance of the classifier. The mAP is the average of AP values of multiple categories. AP is one of the most important performance evaluation indexes to measure the performance of a classifier. As this model only needs to detect the cutters, Average Precision (AP) is adopted as the evaluation standard of the experiment.

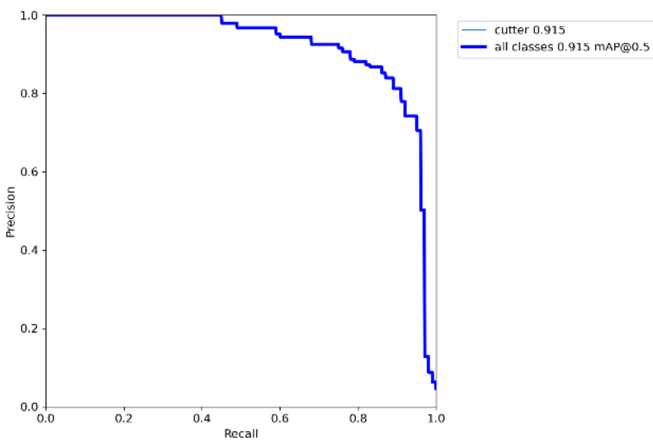

Fig. 3. The Recall(R) and Precision(P) curve of the cutter detection model.

3.3. MODEL TEST

After the training, we need to test the model through our test set. We saved the test set image to the corresponding location and used the model parameters in the file best.pt for target detection.

Here are some of the test results following. Through the test, it can be found that the average object detection time of images using this model is about 0.003s. Also, we can find that the cutter position can be accurately detected by this model. In addition, the model can obtain accurate cutter detection results for different types, different angles and different colors of PDC bits. Therefore, the model has highly universality.

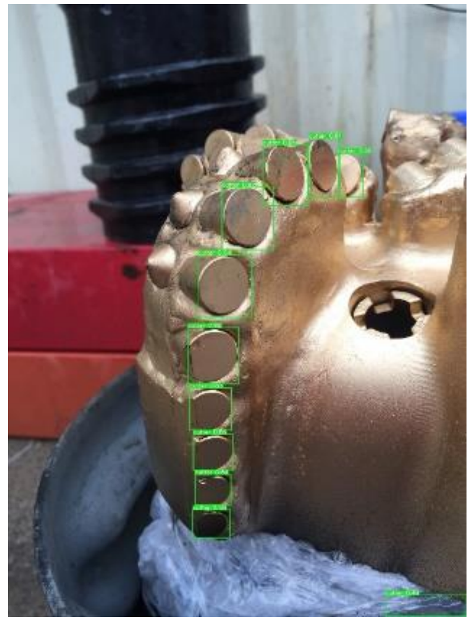

Fig. 4. The cutters detection result based on the training model.

Fig. 5. The cutters detection result based on the training model.

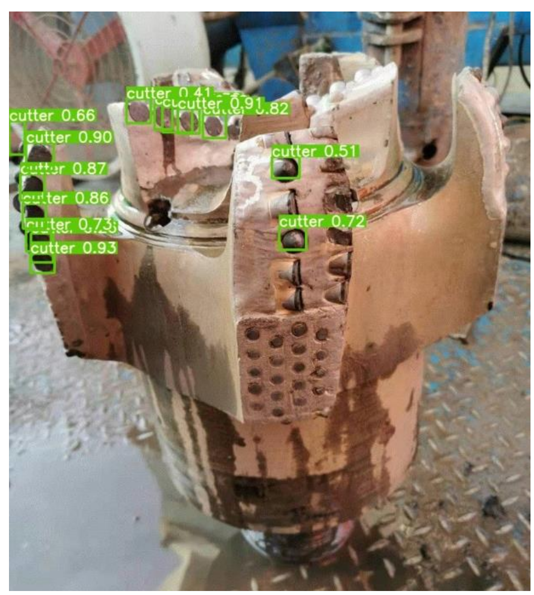

Fig. 6. The cutters detection result based on the training model.

3.4. *WEAR GRADE JUDGMENT*

The single tooth wear degree of PDC bit needs to be judged by the wear level of all the cutters in the tooth. Therefore, after obtaining the position of all cutters in the single tooth, it is necessary to crop each tooth image to get the picture of each cutter and then calculate the wear level of it.

We combine the detection result of single tooth and the picture itself into the corresponding path and use the "CropImage" function.

The "CropImage" function, is a method to crop and save each cutter image according to the position saved in the text file, which has the coordinates of the cutter position, the cutter's width, and height values. By using this method, all cutter positions detected in the corresponding text file are being cut and saved, to obtain each cutter picture of a single tooth. For instance, the crop result of image is as follows:

Fig. 7. The cropped image based on the "CropImage" function.

The wear degree of the single tooth is the sum of the wear degree of each individual cutting tooth. Therefore, we import the image of each cutter into the OpenCV function, which will calculate the wear of the imported single cutter. First, we will do image preprocessing for it, contains graying, image filtration, Gaussian smoothing. After that, we will detect the edge to obtain specific cutter's location in this picture. Then, we obtain the external ellipse of the cutter position to know the initial state of this cutter. By comparing the initial state of the cutter with the current state, the wear degree of the cutter was obtained, and then the wear grade was obtained.

For example, we import the following picture. Then, with the OpenCV method, the final processing images of cutter were obtained by image graying, filtering, Gaussian smoothing and threshold segmentation. The abrading contour of cutter is obtained using contour detection. And the initial contour is obtained by the image of ellipse fitting. The wear proportion, the result we want, was obtained by comparing the two contours covering areas.

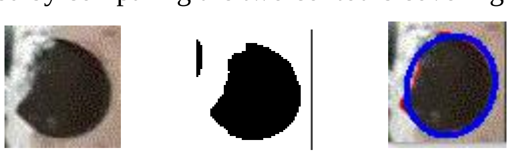

Fig. 8. The PDC bit cutter contour of the initial and current based on OpenCV.

After we get the contour of the initial cutter and the current cutter. We calculated the area of each zone and checked the proportion of these two zones. Based on this ratio, the cutter wear levels are proportionally divided into 8 classes. The area calculation and wear results in this example are as follows:

The initial cutter area is 1720.4066149351422

The current cutter area is 1667.0

The proportion of this cutter is 0.9689569811743861

The wear grade is 1

We got the areas of these two contours and figured out the proportion. With this proportion, we determine the wear of the cutter as 1.

4. CONCLUSION

Based on the particularity of PDC cutter position and the similarity of surrounding environment, a method for obtaining the PDC drill tooth wear grade based on YOLO v5 and OpenCV is proposed in this paper. Firstly, a single-position detection model based on YOLO v5 is trained, including dataset preprocessing, algorithm principal analysis, model training and model testing. After the model is obtained, the single tooth wear degree calculation is performed based on OpenCV, including image cropping, image preprocessing, edge detection, ellipse fitting and wear degree calculation, etc. The system can help operators in the field to acquire real-time wear degree analysis of the PDC bit, only based on the teeth pictures, fast and universally. In terms of the detection of bit wear degree, this system can improve the working efficiency and quality of operators, reduce the risk and bit cost, and improve the level of intelligent automation and digitalization of drilling sites.

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REFERENCES

1. Capik Mehmet & Yilmaz Ali Osman.(2021).Development models for the drill bit lifetime prediction and bit wear types. International Journal of Rock Mechanics and Mining Sciences. doi:10.1016/J.IJRMMS.2021.104633.
2. VV Timonin,AS Smolentsev,I O Shakhtorin... & AS Kushkhabiev.(2017).Causes of wear of PDC bits and ways of improving their wear resistance. IOP Conference Series: Earth and Environmental Science(1). doi:10.1088/1755-1315/53/1/012027.
3. Mazen Ahmed Z.,Rahmanian Nejat,Mujtaba Iqbal M.,Hassanpour Ali. Effective mechanical specific energy: A new approach for evaluating PDC bit performance and cutters wear[J]. Journal of Petroleum Science and Engineering,2021,196.
4. Mahmoud Hassaballah & Ali Ismail Awad(2020).Deep Learning in Computer Vision:Principles and Applications.CRC Press.
5. Redmon, J., & Farhadi, A. (2018). Yolov3: An incremental improvement. arXiv preprint arXiv:1804.02767.
6. Alireza Taheri Tajar,Abbas Ramazani & Muharram Mansoorizadeh.(2021).A lightweight Tiny-YOLOv3 vehicle detection approach. Journal of Real-Time Image Processing(6). doi:10.1007/S11554-021-01131-W.
7. (2020).Real-Time Lane Detection and Object Recognition in Self-Driving Car using YOLO neural network and Computer Vision. International Journal of Innovative Technology and Exploring Engineering(7S). doi:10.35940/ijitee.g1010.0597s20.
8. Andhumoudine, A. B., Nie, X., Zhou, Q., Yu, J., Kane, O. I., Jin, L., & Djaroun, R. R. (2021). Investigation of coal elastic properties based on digital core technology and finite element method. Advances in Geo-Energy Research, 5(1), 53-63.