UDC 629

BOLT RECOGNITION BASED ON NEURAL NETWORKS

Yang Yan, Sophomore doctoral student Ivan Chicherin, Vice professor, doctoral supervisor Chen Qing, Sophomore doctoral student Long Chanjuan, Sophomore doctoral student An Chao, Sophomore doctoral student Xi Tao, Sophomore doctoral student Wu Guangyong, Sophomore doctoral student T.F. Gorbachev Kuzbass State Technical University Kemerovo, the Russian Federation

1. Introduction

The detection of bolt failures has always been of great importance to researchers. In the field of rail transportation, bolts play an extremely important role in fixing the rail[1], As shown in Fig.1. As trains run on the tracks, the load vibrations can easily loosen the bolts, causing safety hazards.



Fig.1. Bolt fastening state
Mingyu Wang's team adopted a localization algorithm based on Kirsch edge detection algorithm and Hough line detection algorithm [2]. It has strong portability and is less affected by shadows, tracking angles and obstacles. Samiul et al improved Shi-Tomasi and Harris-Stephen feature extraction algorithms, and introduced neural network into feature recognition, which improved the recognition accuracy from 83.55% to 93.86% [3]. Stella et al. used wavelet analysis for fastener localization. The classifier adopts multi-layer BP neural network structure for recognition and classification, and has achieved good results [4]. Qi Weiwei et al. introduced the application of deep learning method [5], which is popular in the field of machine learning in recent years, in bolt fastener image detection. In the recognition process, the multi-task learning framework is used to identify and classify, which greatly improves the detection performance and achieves certain results.

In this paper, the neural network is applied to the workflow of image processing. The characteristic parameters of the rail bolt images are input into the neural network model, and the characteristic parameters are learned and trained to identify the characteristics of the failed bolt. This enables it to determine whether a bolt is defective. The introduction of the least mean square filter algorithm optimizes the

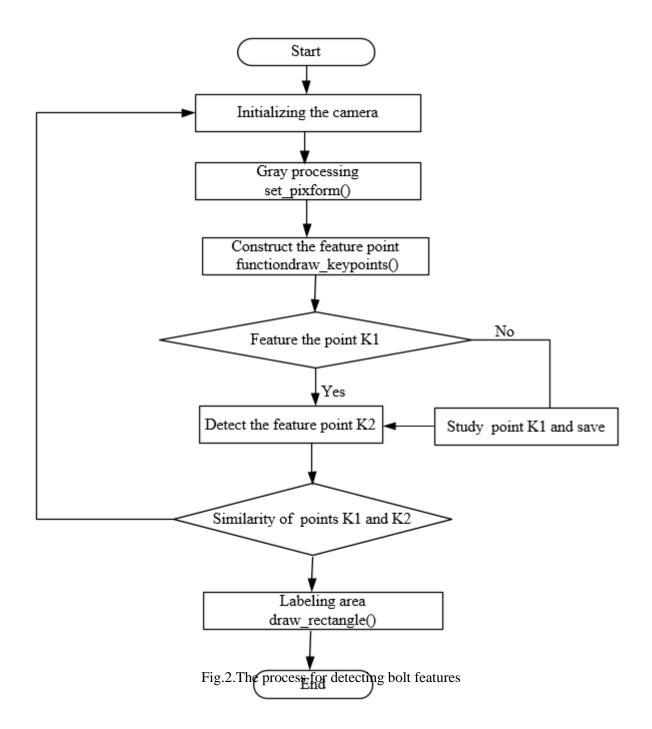
structure of the neural network so that it can perform a global search to obtain a global optimal solution instead of outputting a local optimal solution.

- 2. Design
- 2.1 Workflow of the design

This is a track bolt fault recognition system based on image processing. Firstly, the system used OpenMV to collect track bolt images and obtain the characteristic parameters of track bolts. Secondly, the characteristic parameters are input into the neural network model for fault type identification. Thirdly, the identified results are sent back to the Stm32 micro-controller through the UART serial port for feedback. Finally, after judgment, the Stm32 micro-controller will decide whether to issue a warning. The workflow is described as follows:

- (1) Image acquisition: the track bolt data set was established through OpenMV image acquisition;
- (2) Image pre-processing: the image is gray-scale processed, and the feature points and related feature parameters of the track bolt area on the image are extracted.
- (3) Constructing the neural network model: The structure of the neural network is optimized by using the least mean square filter algorithm
- (4) Building a control system based on STM32:The results of the neural network test are sent back to the Stm32 micro-controller through OpenMV, and the micro-controller makes the decision on whether or not to initiate an alarm based on the test results
 - 2.2. Openmy-based Image recognition system
 - 2.2.1 Feature extraction

In this research, feature extraction is performed based on the shape characteristics of the track bolts. Before feature extraction, the collected images of the track bolts are processed into grayscale. Then a feature point extraction function is constructed to extract and save feature points K1 in the local area of the image. When detecting feature points, the algorithm first determines whether the previous feature point K1 exists. If it exists, it is directly matched with the recognized feature point K2. If it does not exist, the algorithm learns the feature points captured by the camera and saves them as K1, and then detects feature point K2 to compare whether they match. If they match, the consistent features are marked with a cross and rectangle. The flow chart of the specific algorithm is shown in Fig. 2.



The feature detection function used is find_key points(). This function can only run in a grayscale environment because images in RGB mode with too many color variations can cause the failure of extracting effective features for a specific object in the image, thus affecting the success rate of the image processing system in identifying track bolt faults. Therefore, after capturing the image, we need to convert it to grayscale to reduce the interference of image color on the recognition results. The bolt feature extraction and annotation images are respectively shown in Fig.3 and Fig.4.

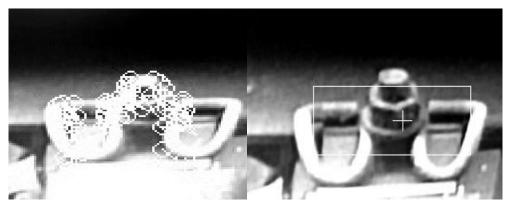


Fig.3.Bolt extraction image

Fig.4.Bolt annotation image

2.2.2.Implementation process and results

The data collected by OpenMV is divided into a training set and a test set. The training set is mainly used for the training process of the neural network, while the test set is used to check whether the neural network model is reasonable. The training process of the neural network can only be carried out after the neural network structure has been determined. During the training process, the feature parameters of the track bolts in the training set are input into the neural network model, and the output results are obtained.

Based on the aforementioned process, 400 images were collected for calculation, consisting of 200 normal bolts and 200 faulty bolts. The data was processed using the Edge Impulse web environment with the data-set being divided into a training set and a testing set. The training set contains 80% of the total training set, while the testing set contains the remaining 20%. the neural network achieved a success rate of 92.5%, This demonstrates that the neural network can meet the operational requirements for identifying faults in rail bolts.

2.3.Control system based on STM32

The control system design based on STM32 is shown in Fig.5. After the motor is started, the photoelectric sensor detects the presence of a track bolt during the motor running process, and feeds back the information to the STM32 micro-controller. The STM32 micro-controller receives the command to stop the stepper motor, and then the OpenMV detects the status of the track fault bolt and transmits the detected information to the STM32 and then determines whether to light up the LED based on the information received.

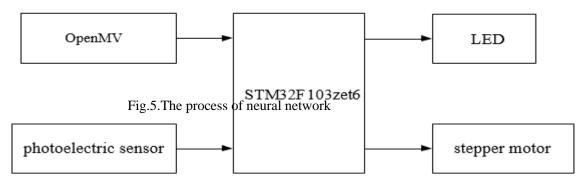


Fig.5.The construction of control system

3. conclusion

The main focus of this study is the development of an image processing based rail bolt recognition system, utilizing hardware such as OpenMV and Stm32. In order to improve the detection rate of bolt failures, it implements neural networks into the image processing workflow, taking rail bolt images as input into the neural network model. Through learning and training the characteristics of bolt images, the neural network can recognize features of bolt failure, possessing the ability to determine whether a bolt has failed.

References

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