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Crack Detection Technology of Subway Tunnel Based on Image Processing

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Abstract: Nowadays, the detection technology of cracks in subway tunnels with increasingly developed rail transit in China is an important research direction. The subway will be a pillar of future traffic, so the safety of subway tunnels is also a top priority. Tunnel cracks are one of the most common problems. In the past, there were many methods for detecting cracks, but each has its own shortcomings, so this paper proposes a new algorithm. The purpose of the experiment in this paper is to identify tunnel cracks by designing an automatic tunnel crack detection system based on machine vision, in order to enhance the image using a combination of Mask homogenization and gray-scale corrosion, and use a Gaussian-fast median filter algorithm A large amount of noise is filtered out, and the crack image is segmented based on the Otsu method, and finally a binary image is obtained. The research results show that the proposed algorithm has a recognition rate of more than 95% for ordinary cracks, and an accuracy rate of 83% for the surface cracks of subway tunnels. Advantage. It is believed that this algorithm will greatly improve the safety of construction and train operation and protect people's lives.

1. Introduction

Nowadays, with the rapid development of our country, the rail transit is gradually on the right track. Subway is one of the most representative means of transportation in rail transit, and it is also the inevitable trend of rail transit development in the future [1]. The subway is often built underground, and the tunnel is the most critical part of it, that is to say, the safety of the subway tunnel is particularly important [2]. In the process of subway construction, there will be many problems, because of various reasons such as temperature, humidity, rock characteristics and so on [3]. For people's safety, these problems must be solved. The purpose of this paper is to use image processing method to detect tunnel cracks [4].

In the construction, the tunnel crack is one of the most common problems [5]. Most tunnels appear in the early stage of tunnel construction, and cracks often occur in the construction process [6]. At present, the crack detection of subway tunnel in China mainly depends on manual visual inspection and manual marking. This method is time-consuming and laborious, subjective and not conducive to the safety assessment of tunnel [7]. In this regard, it is an inevitable trend to replace the traditional methods with automatic crack detection system based on image processing in the development of nondestructive testing of tunnel engineering [8]. The crack detection system based on image processing was first applied in the fields of highway and bridge. With the continuous development of tunnel traffic, scholars at home and abroad began to study the automatic detection system for tunnel cracks.

At present, crack detection based on image processing has achieved many research results. L-Q uses Mask homogenization to balance the light intensity of the image, gray-level corrosion enhances the contrast of the crack, and then designs the feature analysis method to extract the crack, and then detects and analyzes it after extracting the crack [9]. The Gaussian filtering denoising algorithm based on irregular regions proposed by Jung-Bo effectively improves the problem of image detail loss, but the filtering effect of pepper and salt noise is not ideal, but the salt and pepper noise has a greater impact on the image detection results, so there are defects [10]. R. Chen has designed two classifiers for the detection and identification of cracks, one is used to detect cracks and the other is used to determine the type of cracks. The identification methods used for unused cracks are slightly different, so the final detection result It will be more accurate compared to other algorithms [11]. When Jhang splits the cracks, the segmentation threshold is changed by improving the relevant parameters of the original Otsu algorithm. However, the parameters in the algorithm still need a lot of verification for the reliability of different images. This requires a lot of time and is not dominant in time-consuming. It also takes up memory resources of the computer and is not suitable for large-scale testing [12]. Joohyeb uses the minimum path algorithm to detect cracks. The algorithm needs to manually find the crack points, and then track all cracks according to the crack points. It is a semi-automatic detection method, but manually finding the crack points will inevitably be missed and it is easy to ignore some small Crack [13]. General image processing algorithms cannot take into account these problems at the same time. Therefore, this paper proposes a set of algorithms suitable for the detection of tunnel surface cracks.

Simply speaking, this paper discusses the detection technology of subway tunnel crack based on image processing. Specifically speaking, the main research content of this paper is roughly divided into five parts: the first part is the introduction part, which aims to make a systematic overview of the main research content of this paper from the research background, research purpose, research ideas and methods; the second part is the theoretical basis, and a detailed and systematic summary of the current research status of network security information system monitoring technology. The third part is related research, through the query of data and related experiments, the advantages of the image processing-based subway tunnel crack detection technology are described. The fourth part is the analysis of the data and the results after several algorithm processing, and the feasibility of the subway crack detection; the fifth part is the summary and suggestions of this paper, which is the summary of the results of this paper and the prospect of further discussion and analysis of the subway tunnel crack detection technology based on image processing.

2. Proposed Method

2.1. Image Processing Technology and Related Algorithms

Aiming at the complexity characteristic of the crack image on the tunnel surface. In this paper, a preprocessing algorithm combining global and local is proposed to deal with the problem of uneven illumination and low contrast, and a filtering algorithm based on connected regions is designed to filter out a lot of random noise in the image.

In practical engineering applications, due to the limitation of shooting conditions, the tunnel crack image has low contrast [14]. The problem of uneven lighting. This has a great influence on the detection of cracks. To this end, this paper uses two preprocessing processes of gray scale corrosion and local histogram stretching to reduce the influence of these factors [15]. The local histogram first needs to divide the image into blocks. For the sub-images whose boundaries do not meet the side length condition, a new area containing the area is selected in the image. This algorithm uses the normalization of the image, which can reduce the amount of calculation, and also protect the image details and avoid distortion [16]. Then carry on the denormalization again, can get the final result. The process of preprocessing is shown in formulas 1, 2, 3, 4, 5, and 6.

$$G(x,y)=\min\{I(x+x',y+y')-S(x',y')\,|\,(x',y')\in D_s\} \tag{1}$$

$$V_{\mathrm{i}}(x,y)=\frac{U_i(x,y)-\min(U_i(\mathrm{x},\mathrm{y}))}{\max(U_i(x,y))-\min(U_i(x,y))} \tag{2}$$

$$M_i=\frac{1}{W\bullet H}\sum_x\sum_y V_i(x,y) \tag{3}$$

$$L_i(x,y)=\frac{1}{1+(\frac{M_i}{V_i(x,y)})^{\lambda}},V_i(x,y)\neq 0 \tag{4}$$

$$Q_{\mathrm{i}}(x,y)=L_i(x,y)\times 255 \tag{5}$$

$$P_{\mathrm{i}}(x,y)=\begin{cases}0,Q_i(x,y)\leq t_i\\ ,Q_i(x,y)>t_i\end{cases} \tag{6}$$

The next step is to process the noise in the image. The tunnel image is often a variety of different, irregular, disordered, and different forms of noise. These noises seriously affect the crack detection, but the traditional filtering algorithm cannot completely eliminate all kinds of noises [17]. Therefore, this paper proposes a filter algorithm based on connected region.

The first is to find the connected area and its external figure of binary image. By calculating the maximum and minimum coordinates in each connected region, we can get the external rectangle of each connected region. The second step is to use the zero matrix of connected region to filter, and set the threshold value T_n. The number of connected regions is N_{n}, and the filtered image is $F(x,y)$. In the third step, due to the uneven illumination and the influence of the surface texture, there are a lot of block noise in the binary image. The crack is a kind of slender structure, so it can be filtered by the rectangularity of the connected region. The last step is special filtering. After the above filtering, there are only some special noises in the image. The shape of these noises is irregular and does not meet the above filtering conditions. For this kind of noise, this paper uses formula 7 to calculate.

$$E_k(x,y)=\begin{cases}1,\omega_{\max}>T_\omega,h_{\max}>T_h,R_k>T_r\\ 0,\omega_{\max}<T_\omega,h_{\max}<T_h,R_k<T_r\end{cases} \tag{7}$$

2.2. Algorithm of Crack Image Width Measurement

Tunnel crack detection is to detect whether the cracks will affect the normal operation of the train, which can be ignored in the fault tolerance range, which also reduces the workload of workers. In this paper, an algorithm is proposed to calculate the crack width by means of neighborhood mean and standard deviation. The algorithm calculates the crack width at each crack pixel [18]. It is divided into two steps: the first step is to calculate the normal of the neighborhood of the crack point. The algorithm is to select a square neighborhood of the crack points in the crack skeleton map, and then calculate the slope of the line between the farthest two pixels in the neighborhood [19]. The size of the square neighborhood selected in this paper is 55. The second step is to select the neighborhood and calculate the width. Use formulas 8, 9, 10, 11, 12 to calculate.

$$A=(I(x_0,y_0),I(x_1,y_1),\Lambda\ ,I(x_D,y_D),\Lambda\ ,I(x_{2D-1},y_{2D-1}),I(x_{2D},y_{2D})) \tag{8}$$

$$\mu=\sum_{m=a}^{\mathrm{b}} r_m p(r_m) \tag{9}$$

$$\sigma=\sqrt{\sum_{m=a}^{\mathrm{b}}(r_m-u)^2 p(r_m)} \tag{10}$$

$$\mathrm{p}_{k_i}=I(x_{D-k_i},y_{D-k_i}),k=0,1,\Lambda\ ,D \tag{11}$$

$$\mathrm{p}_{k_i}\le\mu-\sigma,p_{k_i+1}>\mu-\sigma,k_1=0,1,\Lambda\ ,D \tag{12}$$

2.3. Gauss Fast Median Filtering

There are many noises in the fracture map, resulting in uneven background distribution [20]. The common noise in crack image detection mainly includes: Gaussian noise generated in the process of image generation and propagation and salt and pepper noise generated in the process of image conversion [21]. Gauss filter can remove Gauss noise very well, but it will blur the details of the image; median filter has a very good filtering effect on salt and pepper noise, and it can also protect the details of the image very well. What is needed for the following feature extraction and segmentation recognition of subway cracks is the edge details of the cracks, but the median filter operation speed is slow. Therefore, this paper also uses Gauss fast medium the value filtering method is used to filter the collected subway crack image [22].

Generally, the pixel value of the neighborhood point of gray image is very close. If the value of a pixel point is quite different from that of its neighborhood pixel point, that is, the pixel value of the point has a sudden change, then the pixel point is the noise point or the edge point of the crack [23]. According to the above principle, Gauss - fast median algorithm is used to filter the image: a 3* 3 filter template is selected to scan each pixel in the image, calculate the weighted mean value of the window, and compare it with the gray value of the central pixel. If the weighted mean value is greater than the central pixel value, it means that this is a noise point, which is filtered by Gauss filter [24]; if the weighted mean value is less than or equal to the central pixel value, the point is considered to be an edge point or a noise point, which is filtered by fast median filter, so as to protect the edge details of the crack within a certain range [25]. The combination of Gauss and fast median algorithm can not only remove a lot of noise, run fast, but also retain the details of the edge. In this paper, the simulation software is used to build the model and detect the cracks.

3. Experiments

3.1. Image Preprocessing

The object of this experiment is to analyze the common crack image, using the algorithm proposed above. The feasibility and validity of the algorithm are tested. In the process of each experiment, there will be a large number of error monitoring data to be processed at any time, and these monitoring data will inevitably have huge errors, so it is very important to choose the appropriate monitoring and processing methods for these data errors.

This paper uses the algorithm and other algorithms to detect the same experimental object. The algorithms are Mask uniform NDHM segmentation algorithm, morphological edge detection algorithm, and the algorithm proposed in this paper. It can be seen that the use of Mask smoothing algorithm can effectively avoid the uneven illumination, but after the smoothing, the noise texture is enhanced at the same time, which leads to false judgment for the later crack extraction, and the direct segmentation cannot remove a lot of noise in the image. The algorithm in this paper solves this problem skillfully. It not only removes the influence of noise, but also filters the background gray of the image effectively, and retains the features of the cracks in the image to the greatest extent. Although there is some noise interference, but within the allowable range of error, it has little impact on the results, and increases the texture recognition rate of the cracks at the same time.

In this paper, the cracks are marked in the original image, and the width of the crack is calculated. In pixels, the maximum width and the location of the entire crack image are marked, and the average width of the image is also calculated. This study mainly calculates the pixel domain image, so the calculation unit is calculated in pixels, as shown in Table 1 below:

Table 1. Crack width comparison

Image number	Company	Average width
1	Pixel points	2.5636
2	Pixel points	2.2146

It can be seen from Table 1 that the maximum width of the two concrete crack images is 11-pixel units, and the average width is 2.7836 and 2.4168 pixels. The next step is to filter and de-noise the acquired graphics, using Gaussian-fast median filter and Otus algorithm respectively. Finally, extract the feature value of the image for judgment.

3.2. Establishment of Experimental Model

After obtaining the crack image information, the important work is to detect whether there are cracks that affect the driving safety from the information, so as to ensure the normal operation of the train and the safety of passengers, and deal with and prevent the dangerous information in time. In the actual work, some work information is often not updated in time, or the detection is not accurate, resulting in mistakes, which will cause unimaginable consequences. The best way is to solve the root cause of the problem. Therefore, it is very important to read the correct tunnel image in time and detect whether the tunnel cracks affect the normal operation of the subway. The relationship between tunnel image acquisition and crack monitoring is a comprehensive information evaluation model. Comprehensive evaluation is the key to tunnel detection. When problems are found, timely feedback is needed to avoid major consequences. Therefore, a comprehensive evaluation model is mainly established in the research of detection model. The purpose of establishing a comprehensive evaluation model is to establish a functional relationship between information evaluation and information reliability, that is, to use the information obtained from various channels to determine the impact of various factors on the required fields, and to establish a functional model to reflect the tunnel cracks in time, using the algorithm proposed in this paper.

The commonly used methods to establish statistical model are stepwise regression, multiple regression, weighted regression and so on. There are many factors that affect the security or reliability of information. In addition, when establishing the information collection model, it is necessary to determine the relevant collection indicators. After establishing the statistical model, the collection indicators can be determined. According to the knowledge of mathematical statistics, when the statistical model based on the least square method meets the Gauss hypothesis and the residual normal distribution conditions, the statistical model is the best unbiased estimation, which can be used for overall estimation and prediction. Under normal conditions, the residual sequence obtained by fitting the observed values will not appear abnormal; if there is abnormal value, it indicates that the instability precursor may occur.

3.3. Algorithm and Steps Adopted in the Experiment

In the subway tunnel surface image detection and a large number of experiments. The following algorithm is adopted. Next, it is introduced in detail. Morphological edge detection uses the contour shape and gradient change to detect the edge information, so the algorithm is not affected by the uneven light and low contrast of cracks, and there is basically no case of missing cracks. However, this algorithm cannot distinguish the edge of crack and noise, and the result contains a lot of noise edge information. If the background or texture of the image is more complex, such as the first three lines of the image, the results will appear large noise, most of which are ductile block noise and connected with the cracks, the subsequent filtering is very difficult, and eventually will cause a lot of false detection. The algorithm proposed in this paper takes many factors into account. It can not only eliminate the influence of uniform illumination and low contrast, but also it is difficult to filter out kinds of noises. The algorithm is proposed for the surface image of subway tunnel, but due to its consideration of many factors and strong applicability, it also achieves ideal results for the traditional image.

Morphological edge detection algorithm can effectively enhance fracture features, which is better than Mask NDHM segmentation algorithm. Fracture features can be proposed obviously, but there are too many noise areas in the background to achieve the final crack detection task. The algorithm proposed in this paper can better deal with the influence of uneven illumination and protect the details of the image. It can effectively filter out a large number of background noise in the tunnel crack image and extract the crack area in the crack image. By comparing with other algorithms, we can see that the algorithm proposed in this paper has a better automatic crack extraction effect on the tunnel crack image. Although there is some noise interference in the recognition results, it does not affect the judgment of the main cracks.

Because there are many burrs in the skeleton diagram, which are short branches, these burrs seriously interfere with the calculation of crack width, Therefore, it must be filtered. In this paper, we use the direction chain code to calculate the length of the burr, and then set the length threshold to filter the branch.

There are three main processes of burr filtering: endpoint and node detection, branch coding and length calculation. The length threshold is set to filter. (1) Node and endpoint detection. The node is the point on the fracture skeleton where the branching begins. The endpoint is the point at the end of the branch and also the point at the end of the branch. From node to endpoint is a complete branch. Take the 3*3 neighborhood of the pixels on the skeleton map. If there are at least 3 pixels in the neighborhood connected with the center point, the center point is a node. For endpoint detection, this paper proposes a new detection method, which constructs 8 templates to traverse the whole image, and takes the skeleton points satisfying the template conditions as the endpoint. Experimental results show that this method can detect any shape, any direction endpoint. (2) Branch code and length calculation. Tracking the crack skeleton from the end point to the end of the node is a complete branch. The direction chain code is used to code the branch, and then the length of the branch is calculated. (3) Burr removal. According to the conditions of the tunnel site and the thinning algorithm, the appropriate length threshold is selected, and the branch whose length is lower than the threshold is filtered as burr.

Next, we start to calculate the width of the crack, and mark it in the original image. This algorithm can use the gray value of the original image to calculate the maximum width and position of the crack feature. The width calculation is also based on pixels. In the future, we can combine the high-precision image calibration technology to convert it into the actual size. After calculation, the maximum width and average width of the crack can be obtained. Finally, the cracks identified will be identified with boxes for the staff to recheck.

Crack length calculation. After the fracture segmentation, the skeleton map is actually to extract the central pixel outline of the target on the image, that is, to refine the image based on the target center. Generally, the refined target is the width of single-layer pixel, and its length is calculated on the basis of the fracture skeleton map. Starting from the long side of the circumscribed rectangle, it is divided into N regions. Calculate the distance between two adjacent center points. Calculate the crack length according to the formula.

Crack width calculation. The calculation of crack width is obtained by combining its skeleton map and gray scale map. Firstly, for each skeleton point, 5multiply5square neighborhood is selected, and the extension line of the square domain is replaced by the line between the two farthest points in the neighborhood. The normal coordinates of each skeleton point are calculated, and the corresponding points of the crack point in the gray image are found, and a straight-line domain is determined in the normal direction of the crack point to calculate the width.

Calculation of crack area. Crack area in pixels. Scan the image crack line by line from the upper left corner, the initial value is 0, if the pixel is the point on the crack, then add 1 automatically. After the scanning, the number of pixel points is the crack area. The minimum external rectangular area of crack. Find out all the points of the fracture contour, then search the points on the contour to find the smallest rectangle of the contour image, determine the length and width, and calculate the rectangular area of the fracture. Feature extraction is carried out for three kinds of fractures, and the length, maximum width, area and average width are shown in the figure below.

After the above process, the final analysis and detection is based on the calculation results.

4. Discussion

4.1. Analysis of Detection Results Based on A Subway Tunnel Crack

In this experiment, a large amount of data can be obtained through the crack identification algorithm and the width calculation algorithm for analysis. Using the algorithm of this paper to calculate the width of the crack and mark it in the original image, this algorithm can use the gray value of the original image to calculate the maximum width value and position of the crack feature in the detected crack area. The calculation also uses pixels as the unit of measurement. In the future, it can be combined with high-precision image calibration technology to convert to actual size. As shown in table 2:

Table 2. Crack width comparison

Image number	Company	Average width	Maximum width
1	Pixel points	3.2153	13
2	Pixel points	4.1423	12
3	Pixel points	3.4324	11
4	Pixel points	3.2145	11

It can be seen from Table 2 that the algorithm can effectively remove most of the noise interference for the subway tunnel image with complex texture, efficiently extract the crack features, and be automatically marked. After the image thinning and glitch thinning algorithms, the crack width measurement algorithm proposed in this paper can be used to calculate the crack parameters in the pixel domain. In this study, about 150 typical crack images of typical subway tunnel images were collected, and experiments were performed using the algorithm proposed in this paper.

This algorithm has conducted detection experiments for different crack types. In the recognition results, while the crack area is recognized, there is a partial misjudgment of the pseudo crack, but the amount of data is small, mainly determined by the texture complexity of the crack image collected. For individual crack images with complex textures, due to various noise disturbances and the coverage of other stains and water marks, more false detections and local fracture phenomena of crack features are caused, but a part of the cracks appear without leak detection. The phenomenon of misdetection is acceptable in the field of actual engineering. The following table is the test accuracy of this algorithm for different cracks. The results clearly show that the recognition rate of this algorithm for different ground cracks, wall cracks, and tunnel cracks is far higher than expected, and the repetition rate and false detection rate are also within the error range. This algorithm is not only applicable to the detection of tunnel cracks, but can also be used to detect cracks on walls or roofs during the construction of houses. This is also one of the major advantages of this algorithm, and its scope of application is wider than that of traditional algorithms. as shown in Table 3:

Table 3. Different crack testing accuracy

Test target	Number of cracks	Recognition rate%	noise factor%	Repetition rate%
Ground fissure	30	92.85	7.42	4.76
Wall cracks	29	94.35	4.67	7.35
Tunnel cracks	52	86.38	8.93	5.53

As can be seen from Table 3, the recognition rate of ground cracks is 92.85%, the false detection rate is 7.42%, the repetition rate is 4.76%, the recognition rate of wall cracks is 94.35%, the false detection rate is 4.67%, the repetition rate is 7.35%, the recognition rate of tunnel cracks is 86.38%, the false detection rate is 8.93%, and the repetition rate is 5.53%.

Generally, we divide the cracks into three types: transverse, longitudinal and reticular cracks, and establish the coordinate system. Set the x-axis along the train running direction and the y-axis perpendicular to the train running direction, then the transverse cracks are parallel to the train running direction, the longitudinal cracks are perpendicular to the train running direction, and the reticular cracks are irregular blocks. After image preprocessing and image segmentation, among the binary images, the one with pixel value of 1 is the crack area, and the one with pixel value of 0 is the background area. The projection method is usually used to judge the fracture type. Because the recognition rate of the projection method is low, this paper improves the projection method by increasing the threshold n, the eigenvalues E1 and E2. As shown in Figure 1.

As can be seen from Figure 1, the projection of the transverse crack in the X-axis direction is relatively gentle, the division is more uniform, and the maximum value of the projection in the Y-axis direction is more obvious. The maximum projection of longitudinal cracks in the X-axis direction is obvious, and the projection distribution in the Y-axis direction is more scattered and relatively smooth. The projection of the network cracks in the X-axis and Y-axis directions is not obvious, and the fluctuation range is similar.

The experiment also tested the accuracy of different algorithms for different situations to evaluate the performance of different algorithms. In total, three different algorithms are used in the experiment, namely the threshold algorithm, the Otus algorithm and the algorithm proposed in this paper. As shown in picture 2.

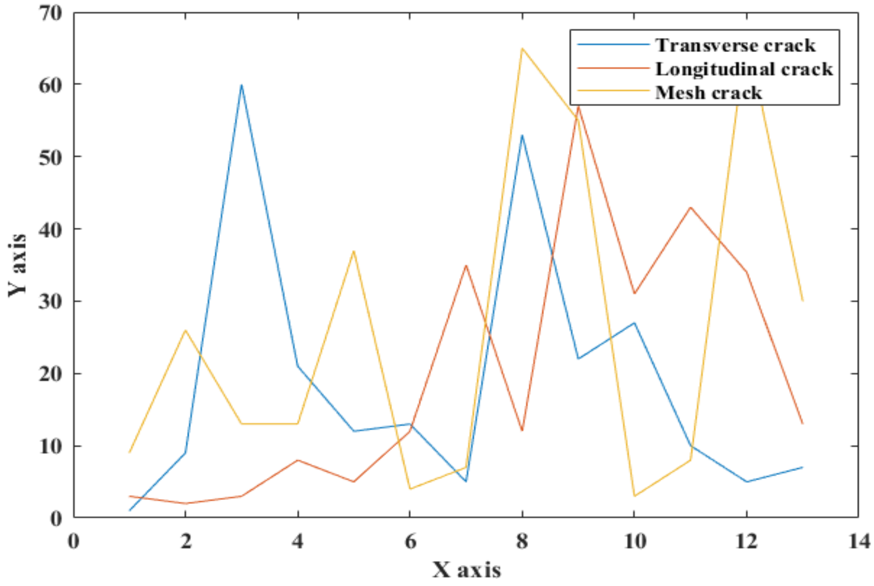

Figure 1. Crack Projection

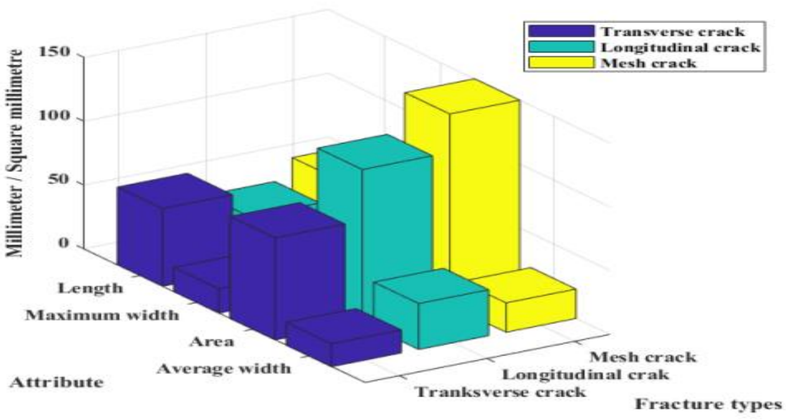

Figure 2. Comparison of fracture eigenvalues

As can be clearly seen from Figure 2, it can be clearly seen that the accuracy of the algorithm proposed in this paper is very high in various situations, all of which are above 80%. The area of the transverse crack is the smallest of the three types of cracks, but the length is the longest of the three types of cracks. The average width of longitudinal cracks is the widest of the three types of cracks, while the length is the shortest, and the area is in the middle. For the network crack, he is the one with the largest area among the three. Because there are many extensions, the area is naturally the largest, but its maximum width is the smallest of the three.

4.2. Eigenvalue Analysis of Subway Crack Image Based on Image Processing

The feature extraction of the crack is also the calculation of the parameters of the crack, usually calculating the length, width and area of the path. The following figure is the analysis results of different algorithms for different crack types, as shown in Figure 3:

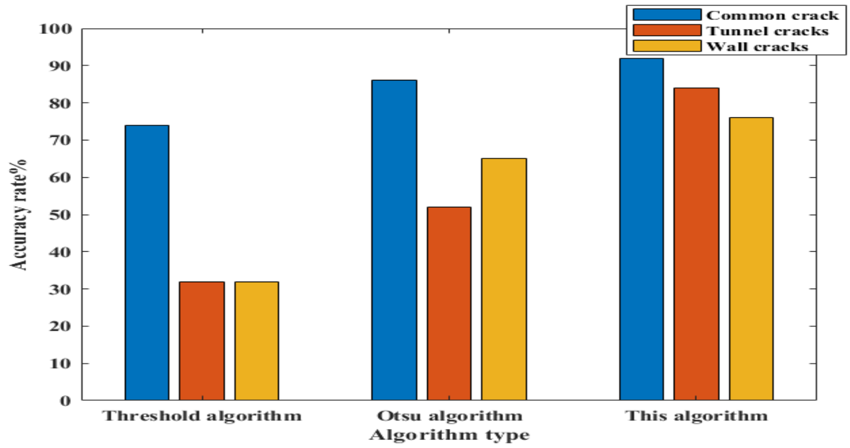

Figure 3. Accuracy of different algorithms for identifying

*As can be s*een from Figure 3, the accuracy of the three algorithms is among the best in identifying and detecting different cracks. The recognition rate of common cracks is over 90%, tunnel cracks are over 80%, and wall cracks are nearly 80%.

Based on this algorithm, different cracks were tested and analyzed, and the analysis results are shown in the figure below. The blue part is the detection number of various types of cracks, and the orange part is the recognition rate of this algorithm for various types of cracks. It can be seen that the recognition rate is about 90%. Compared with other algorithms, the recognition rate is much higher than other algorithms., Which also reduces the possibility of false positives in daily work. As shown in Figure 4:

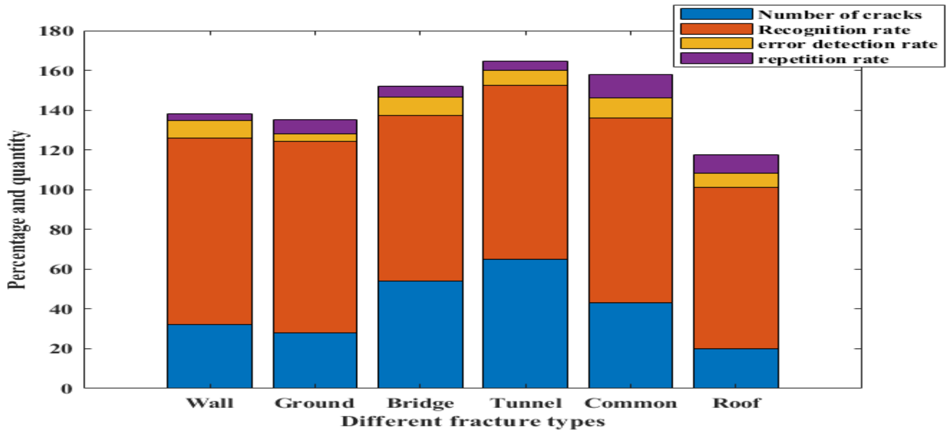

Figure 4. Algorithm for different crack detection rates

It can be seen from Figure 4 that the yellow and purple parts are the false detection rate and the repetition rate, respectively, which are relatively lower than other algorithms. The false detection rate is controlled at about 10%, and the repetition rate is only 5%. The advantage is obvious.

The final analysis is the result of the combination of projection and threshold under the projection method for different crack types. It can be clearly seen that the combination of the projection of the transverse crack and the threshold is the best fit. The transverse fracture fit is the highest, the longitudinal fracture is the second, and the reticular fracture is the last, mainly because the reticular fracture is more complex. As shown in Figure 5:

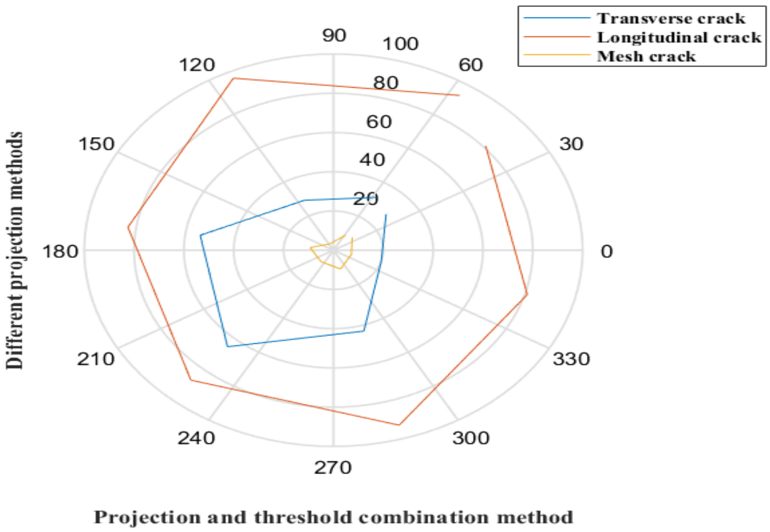

Figure 5. Accuracy of fracture type identification

As can be seen from Figure 5, this article has cleverly solved the deficiencies of other algorithms, and has made great improvements in accuracy, misdetection rate, and repetition rate. The accuracy rate is around 90%, and the repetition rate is reduced to less than 5%.

5. Conclusion

(1) This paper analyzes the common problems existing in the crack detection technology of subway tunnel, and discusses how to solve these problems, and puts forward the corresponding solutions. In view of the shortcomings of traditional algorithms, this algorithm makes up for this deficiency to some extent, and then, according to a large number of practical comparisons, confirms the feasibility of the crack detection algorithm of subway tunnel based on image processing, It also extends the application scope of the algorithm, not only for the detection of subway tunnel cracks, but also to solve the common engineering problems such as wall cracks, deck cracks, roof cracks.

(2) This paper analyzes the feasibility of the subway tunnel detection algorithm based on image processing, puts forward the corresponding working principle and theoretical guidance, and compares it with other algorithms in various aspects. In the aspect of filtering, it can not only remove most common noises like the traditional algorithm, but also remove some special filtering that the traditional algorithm cannot clear. This paper not only expounds the calculation the advantages of this method are also proposed, but in general, this algorithm is better than the existing general monitoring algorithm. And its detection accuracy is about 90%.

(3) The feasibility and excellence of the crack detection algorithm based on image processing are discussed and verified. The experimental results show that the recognition rate of this algorithm is up to 95.5%, which is about 8% higher than that of the general system. The crack detection

algorithm of subway tunnel based on image processing can effectively achieve common crack detection, and achieve a high detection and recognition rate. The guarantee of engineering safety has also been greatly improved.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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