Automatic Crack Detection and Quantification for Tunnel Lining Surface from 3D Terrestrial LiDAR Data

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ABSTRACT

With the rapid development of tunnel engineering, good safety management of tunnels is a research hotspot. As a major factor affecting the safety of tunnels, how to accurately detect cracks has attracted more and more attention of scholars. The traditional crack detection method is manual photography and field recording, which is time-consuming and laborious. It is necessary to develop an automated and efficient crack detection method. In recent years, laser scanning has been used in road crack detection. It is worth trying to introduce it into tunnel engineering on collecting three-dimensional point cloud from the tunnel, and then detect cracks. Therefore, an automatic crack detection method is proposed in this paper. This method can automatically identify the cracks from the tunnel three-dimensional point cloud and extract the crack information. This method combines RANSAC algorithm and LMS algorithm to fit the point cloud surface data, and then expands the cylinder. The improved Alpha Shape algorithm based on Delaunay triangulation is used to extract the crack contour. The limitation of using a single algorithm for cracks extraction is improved in this method. This method is applied to the 36-meters long lining experimental section of the Xiamen Metro Line 3 tunnel and the cracks extraction results were compared with the traditional manual visual inspection. The experimental results show that more than 90% of the target registration accuracy of this method reaches 0.001 m and below. The maximum error of crack width extraction is only 0.20 mm, and the relative error of width and length is less than 8%. The results show that the method is suitable for not only straight but also curved tunnels and can automatically identify serious crack disease information efficiently and effectively.

Keywords: 3D LiDAR; Point Clouds; Tunnel Lining Surface; Crack Detection

INTRODUCTION

By December 2018, the operating mileage of urban rail transit in China has reached 5494.9 km, and the urban rail transit engineering has changed from the stage of “large scale construction” to the stage of “equal emphasis between construction and maintenance” (Zhao & GU, 2019). Tunnel engineering safety accidents occur more frequently. Tunnel lining crack is a common disease that
endangers structural safety, Rapid acquisition and efficient management of tunnel structural surface cracks are significantly crucial to the inspection, maintenance, and safety evaluation of the engineering structure (Yin et al., 2014).

The current practices for the crack detection of the main structure in the tunnel construction and operation are mainly relying on the field record and photographic survey (Liu et al., 2017), which remain time-consuming, labor-intensive, low data quality, and unable to quantitatively obtain the essential geometric information of the cracks (Huang et al., 2012). In the operation stage of subway tunnel engineering, the collection time of regular monitoring data is usually only allowed to complete data collection of more than ten kilometers within a few hours when the train is closed at night, which requires very high efficiency and quality of data collection. These limitations of the current practice make it challenging to meet the requirements of the tunnel construction and its quarterly maintenance inspections (Zhang et al., 2014).

With the development of science and technology, traditional two-dimensional detection technology can no longer meet the requirements of automatic and intelligent detection. Three-dimensional intelligent detection technology has attracted more and more attention of scholars. Three-dimensional (3D) laser scanning, known as “High-Definition Surveying (HDS)”, is a specific form of machine vision (Luh et al., 2013). Kattan et al., (2021) made a virtual 3-D model of the college of engineering/University of Duhok. Kurdistan Region, Iraq. Bhatti et al., (2021) scanned a 4-story public building using a 3D laser scanner to determine the architectural and structural drawings of the response to an earthquake. Zhu et al. (2010) used MAGER 5006i fixed 3D laser scanner to scan the circumferential cracks in the Longxi Water supply Tunnel. Yin et al. (2014) measured the cracks in the 3D point cloud data collected by the Leica HDS6000 fixed 3D laser scanner. Compared with the conventional manual acquisition method, the advantages of automation, rapidness and large-scale application of 3D laser scanning technology provide the possibility for exploring more efficient detection methods of tunnel lining surface crack information. In recent years, three-dimensional laser scanning technology has been used in the deformation monitoring of a few major tunnel projects in the world. The advantages of employing a static Lidar system for geotechnical and operational applications have been demonstrated at a drill and blast tunnel operation at the Sandvika-Asker
Railway Project near Oslo, Norway as well as in two other test tunnels (Fekete et al., 2010). Gikas, (2012) discussed the use and explores the potential of laser scanning technology to accurately track excavation and construction activities of Athens suburban railway system in Greece. Moisan et al., (2015) realized the construction of a full 3D model of a canal tunnel in France by combining terrestrial laser and sonar scans collected from static acquisitions. Saydam et al., (2021) presents a practical algorithm, CFBolt, to detect rock bolts from a 3D laser scanned point cloud and CFBolt was tested for detecting rock bolts from LiDAR scan data collected from Sydney’s civil tunnelling project site.

However, there are many aspects of tunnel detection, how to optimize the three-dimensional scanning technology and better applied and promoted it in all aspects of tunnel engineering still needs more research. Based on the above safety requirements of tunnel construction and operation, this paper will explore a new tunnel lining crack detection method based on three-dimensional scanning technology, and make a useful attempt to better ensure the safety of tunnel engineering.

**LITERATURE REVIEW**

Current studies have developed efficient and reliable algorithms to realize the automation detection of the bridge (Trias et al., 2022). Based on D-S theory, Huang et al. (2014) used the pavement crack detection, the RANSAC (Random Sample Consensus) algorithm, the point cloud coordinates information and the Alpha Shape algorithm to extract the crack outline. The experimental results showed that the method can identify the cracks on the rectangular wood beam and column surface. The Alpha Shape algorithm is inefficient and has obvious limitations in dealing with a large number of engineering point clouds (Cabaleiro et al., 2017). In the studies based on the Delaunay triangulation network (Li et al., 2011), the defective pavement and the normal pavement were distinguished according to the geometric characteristics between the triangular surface of the pavement defect area and the normal triangular surface. Sun (2018) used the Least Mean Square (LMS) algorithm to fit the cross-section line of the road point cloud and determine the position where the crack was located by fitting the wave valley of the curve. However, due to the interference of pavement noise on the LMS algorithm Xu et al. (2014), the estimation results of the crack range were not accurate. Although in the field other than tunnel engineering, the crack detection algorithm based on 3D laser scanning technology has been studied to
some extent, each algorithm still has its limitations.

At present, the research on the automation of 3D laser scanning technology in tunnel engineering is not yet mature. Point clouds do not overlap in many cases (Moisan et al., 2015), which mainsthe point cloud data for tunnel lining surface crack recognition still remains manual (Truong-Hong & Laefer, 2014). Secondly, the research of 3D laser scanning technology algorithms in tunnel engineering is still limited. Based on the fact that the reflection intensity of the point cloud in dry pavement crack was lower than that of the surrounding pavement due to distance and angle, (Yu et al., 2014) proposed an algorithm of extracting crack shape from the 3D point cloud. The extraction results could identify the crack shape, but not the crack width, length, and other key geometric information. Besides, the research on surface fitting algorithms is not yet mature. The tunnel lining surface is curved, and the geometric information cannot be directly measured from the collected point cloud. For the current tunnel lining surface survey, it has been done mainly through processing the 2D (two-dimensional) images or 3D LiDAR point cloud (Qu et al., 2016) to detect the tunnel lining surface and extract useful information for tunnel lining surface crack and leakage by image processing and object recognition (Zhang et al., 2014). Although compared with 2D photography technology, the point cloud data collected by 3D ground laser radar can provide more one-dimensional information in theory, which makes the disease characteristics obvious, the existing photogrammetry machines are bulky and most of them are only suitable for highway tunnel tests. In addition, the types of tunnels currently applicable to tunnel lining surface investigations are susceptible to natural conditions. For example, the tunnel crack is often accompanied by water seepage (Yang & Xu, 2021), the reflection intensity of the point cloud inside the crack is close to the reflection intensity of the surrounding water leakage area. Although cracks with water leakage could be detectable but some cracks closed by white precipitates of calcium carbonate, it is difficult to extract the water leakage crack through the difference of the reflection intensity (Jiang et al., 2019; Xiong et al., 2020). It will be very difficult to identify the surface cracks and other diseases under conditions with limited light sources support (Zhou, 2017). This situation can be effectively improved if the light source conditions are satisfied. Therefore, the study of automatic detection technology in tunnels is still worthy of wide attention.

In summary, although many researchers have studied the deformation information of the tunnel main
structure such as section deformation, clearance convergence, and ellipticity with the 3D point cloud data (Cheng, 2015), the automation research related to cracks (Yin et al., 2014), structural damage, and leakage is still insufficient (Armesto-Gonzalez et al., 2010; Wu & Huang, 2018). Related research has just been carried out in recent years on the crack identification and quantitative extraction of main geometric information, most of them are about highway pavement crack detection. A new method for automatic identification of tunnel lining surface cracks and quantitative estimation of crack size from point cloud data is urgently needed. Therefore, considering the limitations of the above algorithms, this paper proposes an automatic detection and quantification method of tunnel lining surface cracks using 3D laser radar point cloud data. In the proposed method, we first introduced how to properly collect the 3D point cloud data inside a tunnel to ensure data quality and robustness, then prepared the collected raw data through pre-processing, and at last presented how the crack can be automatically identified from the pre-processed tunnel lining surface point cloud and how the crack geometry information could be estimated.

**METHODOLOGY**

In this paper, we are proposing an automatic tunnel lining surface crack detection method to identify the cracks from 3D terrestrial LiDAR data and quantify the size of the identified cracks. The main research framework is shown in Fig.1, the proposed methodology has three major steps, 1) data collection, 2) data pre-processing, and 3) automatic crack detection and quantification. To provide a good quality of data for the third step, we have to start with an accurate and detailed planned data collection and pre-processing process. We established a point cloud acquisition scheme through the systematic analysis of the relationship between crack detection accuracy and scanner parameters, station spacing, and tunnel geometry. With the collected and pre-processed data from steps 1 and 2, we integrated the RANSAC algorithm, the LMS algorithm, and the Alpha Shape algorithm to remove outliers and noise, fit the surface model, and detect crack outlines. This chapter will explain the principle of the method used.

**Fig. 1 Framework of the Proposed Research Methodology**
Data Collection

A tunnel is an ultra-long linear structure, point cloud data collection inside the tunnel is challenged by the scanning angle of view, scanning distance, and scanning accuracy of the 3D terrestrial laser scanner. Therefore, it is necessary to divide the whole tunnel into several scanning stations along the tunnel axis, and targets are used during the data collection for registering all the scans. The key aspects of data collection are the setting of station spacing, scanning resolution, and target placement, which affect the accuracy and efficiency of the 3D point cloud data collection process. The station spacing is set according to the inner diameter of the tunnel and the maximum incident angle of laser reasonably (Wang et al., 2013). As shown in Fig. 2(a), each scanning station is set up at the central axis of the tunnel. For station 2, the measuring point with the maximum incident Angle is located at endpoint B. The maximum incident Angle $\theta_{\text{max}}$ of the laser within the scanning range of station 2 can be calculated based on the geometric relations:

$$\theta_{\text{max}} = \arctan \frac{S}{D} \quad (1)$$

Where S is the station spacing (m), D is the inner diameter of the tunnel (m). For the relationship between S and D, considering the complex ground environment in the tunnel construction site, and other factors, it is difficult for the center of the scanner to locate on the axis of the tunnel center. Through the findings from the recent studies (Tang et al., 2007), we take $S = (1-2)D$.

![Fig. 2. Schematic diagram of station setting and registration scheme](image)

Fig. 2(b) is a commonly used bistatic registration method: arranging the targets in the connecting part between two adjacent stations. At the time of registration, one scanning station is selected as the reference station, and the other stations are registered with the adjacent previous stations respectively. However,
with the increased times of registration needed, the registered data of the long-narrow tunnel structure can be deformed seriously. To solve this problem, Kang et al. (2013) proposed a global registration method to divide the tunnel into different sections, and each section contains a number of stations, and the targets arranged at both ends of the section are used as the common registration control point for each station in the corresponding section. At the same time, Becerik-Gerber et al., (2011) also found that the measurement error of the target is independent of the measurement distance. Therefore, it can be seen that the length of the section can be determined based on the ground environment, visual conditions, required point cloud density, scanner parameters, and so on. In the global registration method shown in Fig.2(c), every three stations are defined as a section, and three stations in the section are registered in the same coordinate system with common control points. The point cloud data of the three stations in the section is integrally controlled. With the incident angle from the laser to the center of the target reducing, it is more beneficial to accurately obtain the coordinates of the center of the target and reduced the point error of the control points. It could reduce the number of control points, which reduces the cost of labor and material costs in the data collection process and improves data collection efficiency.

**Data Pre-Processing**

The purpose of point cloud data pre-processing is to prepare the collected point cloud data and make them ready for the later step - tunnel crack detection. In this paper, we process the collected data in Cyclone 9.0, through which we can perform database creation and import, point cloud registration, point cloud de-noising, Region of Interest (RoI) extraction, and so on. At the end of pre-processing, a text file (.txt format) is generated for the next step.

**Point Cloud Registration**

Unifying the point clouds of different sites into the same coordinate system is called point cloud registration (Becerik-Gerber et al., 2011). Rigid body transformation such as translation and rotation done in the point cloud registration without distortion and scaling. The method of point cloud registration can be mainly categorized into three groups, target-based stitching, targetless based stitching, and mixed stitching. Because the tunnel structure is linearly narrow, there are no obvious characteristic points in the point cloud data. To ensure the efficiency and accuracy of registration, target-based registration is adopted in this research.

**Point Cloud De-noising**

The original point cloud contains a lot of noise data. For mixed points, the RANSAC algorithm is used to eliminate point cloud noise in surface fitting and then fits the optimal model to obtain the effective local point set after eliminating the influence of external points. Finally, the LMS algorithm is used to fit the effective local point set.
RoI Region Selection

Next, to avoid the high computational complexity of global surface fitting of tunnel point cloud (Chen, 2016) and effectively reduce the computing calculation cost and improve the accuracy of surface fitting in the local area where the crack is located, we adopt the local surface fitting to the RoI where the crack is located (Cabaleiro et al., 2017). After selecting the RoI areas, we convert the point cloud in the RoI area to a text format file which can be analyzed by the proposed tunnel detection algorithm for further data processing.

Crack Detection from Point Cloud

Surface fitting of point cloud data

In this step, we integrated the RANSAC algorithm and LMS algorithm to fit the point cloud surface data, which is more robust and accurate than the traditional fitting method (Wei & Liu, 2014). Firstly, the RANSAC algorithm is used for the sampling iterative fitting to obtain the best estimation model and the effective local point set corresponding to the model. In this process, it performs data de-noising and outliers removal. Then, the LMS algorithm is introduced to fit the effective local point set of the best estimation model, so that the algorithm is not affected by the external points and the points with large errors in the data, and could obtain the fitting model which is closer to the ideal model. The flow chart of the algorithm is shown in Fig.3.

![Flowchart of surface fitting method combined with RANSAC algorithm](image)

This paper uses the LMS algorithm for the optimal model. At this time, the observed data are no longer the original sample data, but the data after eliminating certain local points by the RANSAC algorithm. The process reduces the external points and noise in the data and improves the accuracy and rationality of the fitting results greatly.

Crack point clouds removal and extract

After the curve fitting of the point cloud on the lining surface, the point cloud collected in the crack
still exists, which will affect the geometry extraction of the subsequent cracks. Therefore, it is needed to remove the point cloud inside the crack. After the removal, the point cloud is projected and expanded onto the fitting surface, and the 3D point cloud is then transformed into a 2D plane. Fig. 4 shows the removal process of the point cloud inside the crack. L is a critical value defined by the 3D LiDAR scan parameters, as shown in equation 2 (Cabaleiro et al., 2017):

\[ L = \sigma \alpha_c \]  

Where \( \sigma \) is the accuracy of 3D LiDAR, and \( \alpha_c \) is the range value obtained through multiple tests.

![Fig.4. Point cloud removal process inside the crack. (a) Front view of crack point cloud; (b) Side view of the fracture point; (c) Remove points beyond the critical value; (d) Side view after the removal](image)

After the crack point cloud is removed, the cylindrical surface is projected and expanded to a planar surface. The principle of point cloud projection and expansion is shown in Fig. 5(a). With cylindrical section fitting center \( \text{O}(x_0, z_0) \) as the center, projecting all points to the algorithm fit surface is shown by the solid line in Fig. 6. The projection result is expanded along the top of the fitting surface, and the 3D point cloud is converted to a 2D plane. In Fig., \( P = (x, z) \) is a point in the point cloud, \( P' = (x', z') \) is the point projected by \( P \), and \( P'' = (x'', z'') \) is the point after \( P' \) is expanded along the top of the fitting cylinder. \( \text{OA} = (1,0) \) is the positive X-axis unit vector, and \( \text{OB} = (0,1) \) is the positive z-axis unit vector.

![Fig.5. (a)Point cloud projection and expansion diagram Crack outline recognition and geometry extraction (b) The diameter of the circumferential circle and its geometric outline formed by edge points (Cabaleiro et al., 2017)](image)

After the cylinder expansion, we use the improved Alpha Shape algorithm based on Delaunay triangulation to extract the outline of the crack. The algorithm first performs an incremental insertion method to construct the Delaunay triangulation network and then checks whether each edge of the
triangulation network conforms to the conditions of Alpha Shape in turn. After the circle center coordinated the outer circle diameter, $D_\alpha$ of the edge is calculated according to the Distance Intersection Method (Cabaleiro et al., 2017), which measures the distance from the remaining points to the center of the circle. If the measured distance is greater than $D_\alpha/2$ (the radius), the circumscribed circle does not contain the remaining points, and the edge is the Alpha Shape edge. All Alpha Shape edges meeting the requirements constitute the outlines of the crack. As shown in Fig.5(b), the area recognized by Alpha Shape is the sum of the area of all triangles.

FIELD EXPERIMENT AND RESULTS

Point Cloud Data Collection

Wujanz et al., (2017) exclusively investigated including phase-based range finder, Riegl VZ-400i pulse scanner, and Leica scanning station P40 using hybrid ranging strategy. Research showed that since the stochastic characteristics of these laser scanners can also be described by intensity-based stochastic models, their generality was assured. The parameters of Leica P40 3D laser scanner is as follows: Range accuracy:1.2mm+10ppm, Angle accuracy: Angle accuracy 8”/8” (vertical/horizontal), range noise: noise accuracy 0.4mm @10m, target acquisition accuracy 2mm (Wujanz et al., 2018). With the horizontal and vertical resolution of 2 mm for a distance of 2 m (Piech et al., 2018), Leica P40 is suitable for this case study. Based on the above research, in order to validate the feasibility of the proposed methodology, we used a Leica P40 3D laser scanner to scan a section of Xiamen Metro Line 3.

The inner diameter of the measured tunnel segment was known as 5.5m and the width is 1.2m. For this experiment, we selected a section of 36m as the testing object and used MATLAB to implement the proposed methodology. The 3D model for analyzing the diagram of segment lining is shown in Fig.6.

![Fig.6. 3D model of tunnel lining](image)

Because the inner diameter of the tunnel was $D=5.5$ m, according to the calculation method of station spacing in section 3.1. In the data collection process, the distance between two stations was set as $S = 6$ m, that is, the width of 5 segments. To arrange the location of the targets for the registration, we divided the 36-meter-long testing section into two isometric sections. Each section was then divided again into three scanning stations and had three targets set at both ends of the section as the common
registration control points. Two targets were used at the junction of the two sections as the registration control points of the two sections. The detailed layout of the scanning station, target location, and registration scheme is shown in Fig. 7 by considering how to easily set up the target and meet the requirement of no less than two targets between every two adjacent scans. Fig. 8 shows the Leica P40 and two targets in the tested tunnel.

Results and analysis of the preprocessing of the testing point cloud data

In the experiment, we pre-processed the collected point cloud data in Cyclone 9.0. Through the establishment and improvement of the database described in section 3.2, we carried out the point cloud registration, point cloud denoising, and RoI area extraction in turn. The pre-processing results are shown in Fig. 9. Finally, the pre-processed data was exported as a text file for crack detection in the next step.

The analysis results of the pre-processing showed that more than 90% of the target registration reached an accuracy of 0.001m or less, and the rest was 0.002m, which met the requirements of registration accuracy as a whole. The registration accuracy of 0.002m appeared at both ends of the section because only one target was provided at both ends of the section. Therefore, for the future experiment, the number of targets at both ends of the section should be set to two to three to control the overall registration accuracy.

In the experiment, we selected three different cracks with good quality for the crack detection
accuracy analysis manually. Among three cracks, the length of crack 1 was small, the width is larger, the length of crack 2 was larger and the width was small, while crack 3 was small and in an irregular shape. Crack1 and crack2 were also accompanied by obvious water leakages, and the reflection intensity of the collected point cloud was higher in the leakage area. The crack detection results of the RoI region were shown in Table 1. Exporting the “x, y, z” The 3D coordinates of each crack RoI were exported and converted into a text format.

<table>
<thead>
<tr>
<th>Table 1. Crack RoI region extraction</th>
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<tbody>
<tr>
<td>No</td>
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<tr>
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</tr>
<tr>
<td>Picture</td>
</tr>
<tr>
<td>RoI</td>
</tr>
</tbody>
</table>

**Results and analysis of the tunnel crack detection and quantification**

The experiment continued with processing the preprocessed point cloud data from the previous step. The surface fitting algorithm by integrating the RANSAC algorithm and LMS algorithm was used to fit the surface of the RoI region. The absolute fitting errors were estimated as $6.59 \times 10^{-4}$, $1.50 \times 10^{-3}$, $6.90 \times 10^{-4}$ is dimensionless. According to Equation (2), the points beyond the distance $L=0.002$m of the fitting surface were considered as the internal point of the crack and removed. The surface expansion diagram of the remaining points was projected to the fitting surface. The results of the crack surface fitting and cloud projection expansion are shown in Table 2.

<table>
<thead>
<tr>
<th>Table 2. Results of crack surface fitting, projection expansion and extraction</th>
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<tbody>
<tr>
<td>NO.</td>
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<tr>
<td>---</td>
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<tr>
<td>Crack 1</td>
</tr>
<tr>
<td>Crack 2</td>
</tr>
</tbody>
</table>
Then, we continued to extract the crack geometry information by using the improved Alpha Shape algorithm based on the Delaunay triangulation method. The minimum area value was set as $A_{\text{min}} = 5.0 \times 10^{-5} \text{m}^2$. The extraction results of crack outline and geometric information were summarized in Table 2. We then analyzed the crack detection accuracy by comparing the extracted crack length and width in the experiment with the manual close-distance measurement by steel tape and crack width detector. The statistics and analysis of crack extraction accuracy are shown in Table 3.

<table>
<thead>
<tr>
<th>NO</th>
<th>Length Extraction Results</th>
<th>Measured Value</th>
<th>Absolute Error (mm)</th>
<th>Relative Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L1 (mm)</td>
<td>L2 (mm)</td>
<td>$S =</td>
<td>L1 - L2</td>
</tr>
<tr>
<td>1</td>
<td>152.7</td>
<td>161</td>
<td>8.3</td>
<td>5.16</td>
</tr>
<tr>
<td>2</td>
<td>360.2</td>
<td>398</td>
<td>37.8</td>
<td>9.50</td>
</tr>
<tr>
<td>3</td>
<td>163.2</td>
<td>176</td>
<td>12.8</td>
<td>7.27</td>
</tr>
<tr>
<td>Average</td>
<td>—</td>
<td>—</td>
<td>19.63</td>
<td>7.31</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>NO</th>
<th>Maximum Width Extraction Results</th>
<th>Measured Value</th>
<th>Absolute Error (mm)</th>
<th>Relative Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.52</td>
<td>5.72</td>
<td>0.20</td>
<td>3.50</td>
</tr>
<tr>
<td>2</td>
<td>1.64</td>
<td>1.77</td>
<td>0.13</td>
<td>7.34</td>
</tr>
<tr>
<td>3</td>
<td>0.60</td>
<td>0.64</td>
<td>0.04</td>
<td>6.25</td>
</tr>
<tr>
<td>Average</td>
<td>—</td>
<td>—</td>
<td>0.12</td>
<td>5.86</td>
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</table>

It can be seen from Table 3 that the average relative error of the three sets of data is 7.31% for the maximum length of the crack. For the maximum crack width, the average relative error of the three sets of data is 5.86%. The error range is within 8%, which proves the feasibility of the method to a certain extent.

**DISCUSSIONS**

With all the results from the experiment, we performed a statistical analysis of the 36-meters long lining experimental section of the Xiamen Metro Line 3 tunnel and compared it with the traditional manual visual inspection statistical table of crack information, and the comparison results are shown in Table 4. We found out that the results of the manual inspection could only provide the approximate location and the type of cracks. However, our proposed crack detection method could offer the exact location mark of cracks in the tunnel and the estimated value of the crack length and width through the detection with a relative error within 8%, which is within the commonly acceptable error range of the inspection professionals. Crack No.6 cannot recognize the corresponding geometric information because the cracks’ width is less than the acquisition accuracy.
According to the comparison and analysis of the crack geometric information extracted based on our proposed method with the manual inspection results, it can be seen that:

(a) Although the relevant geometric information could not be extracted for the microcracks due to various factors, it still meets the requirements of the current relevant regulations in countries. The conventional manual visual inspection method adopted by the stakeholders can only record an image of the identified lining crack and a description of the corresponding crack without specific dimension information.

(b) The maximum measuring point spacing in the cloud is $\delta_{\text{max}} = 0.5\, \text{mm}$. In theory, this data collection scheme can obtain the crack information of tunnel lining surface which width larger than 0.5mm. The experimental results show that the proposed algorithm can extract the crack width information with a minimum width of 0.6mm, which is consistent with the theoretical analysis. According to the

<table>
<thead>
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<th>Table 4. The comparison between manual crack inspection and automatic crack detection from point cloud</th>
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<tbody>
<tr>
<td>Manual Visual Inspection</td>
</tr>
<tr>
<td>NO.</td>
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<td>---</td>
</tr>
<tr>
<td>TYGP-011</td>
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<tr>
<td>TYGP-015</td>
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<td>TYGP-016</td>
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</table>

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classification standard of the width of the cracks in the tunnel lining (Lai et al., 2015), crack width larger than 0.5mm is Class A crack, which indicates that it is a serious issue. The proposed method can extract the geometry information of the cracks with serious status. With this extra information, the project manager can take proper repair and treatment actions for cracks in different widths, and provide specific data for the related grading evaluation of the influence of cracks on the construction quality and risk of the tunnel structure.

**CONCLUSIONS**

This paper introduces a new method of crack detection of tunnel lining surface from 3D terrestrial laser scanner data. This method was applied to the lining experimental section of the Xiamen Metro Line 3 tunnel and the cracks extraction results were compared with the traditional manual visual inspection. The conclusions are drawn as follows:

1. Target-based registration adopted in this research can meet the registration efficiency and accuracy. We divided the testing section into two isometric sections. Each section had three targets set at both ends of the section as the common registration control points. Two targets were used at the junction of the two sections as the registration control points of the two sections. The analysis results of the pre-processing showed that more than 90% of the target registration reached an accuracy of 0.001m or less, and the rest was 0.002m, which met the requirements of registration accuracy as a whole.

2. Within the allowable range of accuracy, this method is more efficient and time-saving than the manual detection method, and can replace the manual detection method to a certain extent. The comparison results with the manual detection method show that the maximum error of crack width extraction is only 0.20 mm, and the relative error of width and length is less than 8%.

3. The method proposed in this paper is suitable for not only straight but also curved tunnels. The case used in this paper is curved cracks. Cylindrical projection is involved in the application process. The straight tunnel does not need to carry out surface expansion so that the straight tunnel crack is simpler and can also be detected by this method.

4. This method makes up for the limitation of single algorithm. The combination of the LMS, RANSAC, Alpha Shape and Delaunay Triangulation algorithm improves the accuracy of crack extraction. The extracted data is no longer the original sample data, but the data optimized by
the comprehensive algorithm.

This method realizes the automatic extraction of tunnel cracks. However, this method still has limitations. In the case study, we choose the conventional tunnel. The applicability of this method in tunnels with complex working conditions still needs further research and improvement. In addition, in the process of selecting the seepage crack acquisition, the area with better light source contrast intensity is selected, and the extraction accuracy of the crack area with poor light source contrast still needs to be optimized.

The crack detection method proposed in this paper is mainly the automatic extraction of crack geometric information. How to comprehensively utilize the point cloud coordinate information, color information and reflection intensity information of the target object obtained by the three-dimensional laser scanner under the consideration of the surrounding environment is the future research direction. In addition, the existing scanning equipment is large in size. How to apply the excellent technology of large equipment to miniaturized equipment for more portable tunnel crack scanning is a very innovative and meaningful research.

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