Road Tunnel Detection Robot and Method Based on Laser Point Cloud

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Abstract. The maintenance of road tunnels is more important, and there are problems such as water seepage, surface cracking and falling off. If it cannot be detected and handled in time, it will pose a major threat to the driving safety of road vehicles. Therefore, this paper proposes a road tunnel defect detection scheme based on laser point cloud. Firstly, a robot for road detection is developed. Secondly, a road defect detection method based on laser point cloud is developed. Laser SLAM technology is used to reconstruct dense point clouds in road tunnel scenes. Finally, through the automatic detection of the three-dimensional reconstruction scene of the tunnel, the defects such as cracks and spalling of the road tunnel are automatically identified. Compared with the visual detection scheme, this method does not depend on the problem of ambient light and has better robustness and practicability.

1. Introduction
China has a vast territory and a huge number of kilometers of highways. By 2019, China’s total mileage of highways has reached 4.846 million kilometers and its expressways have reached 142,600 kilometers, ranking first in the world. In addition, most parts of China have rugged terrain, with hills and hills accounting for more than 67% of the total area. In addition, rivers and other rivers need to build tunnels to reduce the total number of kilometers of roads and improve transportation efficiency. Among them, as of 2017, the longest road tunnel in China is over 20km in length. However, because road tunnels are built under water, underground or in mountains, they will be affected by changes in the earth's crust, resulting in cracks, spalling and water seepage on the tunnel surface. Therefore, the detection of road tunnels is a major issue related to road safety. At present, road tunnel detection is mainly manual, with some auxiliary instruments. The main problems of manual inspection include: 1. The inspection efficiency is low; 2. The patrol inspection error rate is relatively high, and missed inspection and wrong inspection occur from time to time. It is mainly affected by the experience and attitude of the testing personnel. Therefore, there is an urgent need for an automatic and intelligent detection scheme to replace manual inspection.

At present, inspection robots in various scenes have achieved many applications in replacing manual inspection. For example, Japan proposed using helicopters to inspect high-voltage lines[1]. Climbing high-voltage line inspection robot proposed by Shenyang Institute of Automation, Chinese Academy of
China University of Mining and Technology proposed an inspection robot for underground coal mines. The robot has an explosion-proof design and can detect gas concentration and feed back audio, video and other information. In terms of road tunnel detection, the road tunnel detection equipment manufactured by Hanyang University in South Korea adopts a linear array camera with 4096 pixels CEL/LINE, light source, automatic focal length adjustment equipment, shock absorber and encoder, etc., with a detection speed of 5km/h, and is expected to identify cracks with a width of more than 0.3 mm. The road detection equipment designed by Japan's Road Robot Research Institute (RTRI) in 2007 uses a plurality of linear array cameras combined with a plurality of lighting modules to detect tunnels at a speed of 10-30Km/h with a detection accuracy of about 0.8 mm. The MIS&MMS tunnel detection system proposed by Japan Measurement and Inspection Corporation in 2010 consists of one vehicle body, two detection systems MIS (Mobile Imaging Technology System) and MMS(Mobile Map System). The MIS detection system consists of 20 CCD cameras and 60 sets of LED lighting equipment. The detection speed can reach 80km/h and detect cracks of 0.2mm/Pixel. Tunnelings, a tunnel detection device developed in Spain in 2013, has a detection speed of up to 40km/h and detects cracks of 0.5 mm. Switzerland designed TCRACK in 2012, which is installed on rail cars and powered by rail cars to test subways and railway tunnels. The detection speed is 2.5km/h per month, and cracks larger than 0.3mm can be detected. In 2013, Huang Hongwei and others of Tongji University designed an integrated rapid detection vehicle for highway tunnel structural diseases. Through the integration of linear CCD industrial camera, infrared thermal imager and ground penetrating radar, the vehicle has realized the synchronous integrated detection for tunnel cracks, seepage water and holes. The detection minimum sizes for detecting cracks, water leakage and cavities are 0.3mm, 4.5cm*4.5cm and 12cm*12Cm respectively, the detection speed can reach 5-10km/h, the width range of a single detection tunnel parallel to the axial direction of the tunnel is 2cm, the full range detection of the lining over 1m on the road surface can be realized through multiple walks, and the work is stable and reliable. The vehicle-mounted tunnel lining shed detection system proposed by Wang Rui et al. of Southwest Jiaotong University in 2012 uses 5 DALSA Piranha3 series cameras to build the system. The detection accuracy is designed to identify 0.2mm cracks and the detection speed is designed to reach 13km/h. The tunnel gauge size measurement system designed by Li Peng and others of Beijing Jiaotong University in 2006 uses 11 CCD cameras to build the tunnel gauge size measurement system, which collects 25 images per second. The system is discontinuous detection, and the faster the detection speed, the larger the image interval. When the detection speed is 70Km/h, the image interval is greater than 0.78mm.

Through the above analysis, we can see that the current road tunnel detection is still mainly based on visual detection, which has huge data, high cost and slow processing speed. Therefore, this paper proposes to use laser three-dimensional point cloud to detect tunnel defects, and at the same time, to use the more advanced SLAM technology to improve the detection efficiency of the detection robot. Laser point cloud technology is widely used in the mapping and reconstruction of three-dimensional objects. It is characterized by high mapping accuracy, small amount of data compared with vision, insensitivity to illumination, and sufficient scene modeling information. Laser point cloud reconstruction is mainly divided into laser point cloud data preprocessing, including denoising, simplification and other steps, and finally three-dimensional scene reconstruction is carried out to obtain a more accurate detection model.

Facing the detection of road tunnels, this paper proposes to use tunnel detection robot as the carrier and laser 3d scanner as the main tool to obtain the three-dimensional scene model of road tunnels and provide basic work for the identification of tunnel defects in the future.

The work of this paper is organized in the following order: The second part introduces the basic design scheme of road tunnel inspection robot; The reconstruction method of laser point cloud is introduced in the third part. The fourth part is the discussion and analysis of experimental data. The last part is the conclusion.
2. Inspection Robot

This paper proposes a kind of mobile body that can hang rails and walk automatically in the highway tunnel. It can carry various sensors for tunnel detection to realize the detection of the highway tunnel. Its main technical indexes are as follows:

1. Operating speed: ≥1 m/s
2. Operating voltage: 24V
3. Bearing capacity: ≥20 kg
4. Body weight: ≤4 kg
5. Body size: ≤ 1.0 m × 3.5 m × 1.5 m.
6. Protection grade: IP67

A vision camera and a laser scanner are mounted on the robot body, so that the advantages of the laser scanner, such as insensitivity to illumination, self-provided ranging information and relatively small data amount, are utilized, and the inspection efficiency of road tunnel defects is improved.

3. Reconstruction by 3D Point Cloud

Based on the extended Kalman filter, we estimate the robot motion state and three-dimensional environment point cloud simultaneously. Firstly, the motion of the robot is modeled, and the motion model is expanded to an extended state vector:

\[
y_i = y_{i-1} + \begin{pmatrix}
\frac{v_i}{\omega_i} \sin \theta + \frac{v_i}{\omega_i} \sin \left( \theta + \omega_i \Delta t \right) \\
\frac{v_i}{\omega_i} \cos \theta - \frac{v_i}{\omega_i} \cos \left( \theta + \omega_i \Delta t \right) \\
\omega_i \Delta t + \gamma_i \Delta t \\
0 \\
\vdots \\
0
\end{pmatrix}
\]

(1)

The variables \( x, y, \) and \( \theta \) denote the robot position and pose. The variables \( v_i \) and \( \omega_i \) are the linear velocity and angular velocity of the rigid body. Because the motion only affects the robot’s pose and all landmarks remain where they are, only the first three elements in the update are non-zero. Adding model error estimation to establish a motion model with error estimation:
\[
\mathbf{y}_t = \mathbf{y}_{t-1} + \mathbf{F}_x^T \begin{pmatrix}
-\frac{v_t}{u_t} \sin \theta + \frac{v_t}{u_t} \sin \left( \theta + \omega_t \Delta t \right) \\
\frac{v_t}{u_t} \cos \theta - \frac{v_t}{u_t} \cos \left( \theta + \omega_t \Delta t \right) \\
\omega \Delta t
\end{pmatrix} + N \left( 0, \mathbf{F}_x^T \mathbf{R}_x \mathbf{F}_x \right) \tag{2}
\]

Here \( \mathbf{F}_x \) is a matrix that maps the 3-dimensional state vector into a vector of dimension 3N + 3. In addition, the measurement estimation error model based on normal distribution is:

\[
z^i_t = \begin{pmatrix}
\sqrt{(m_{j,x} - x)^2 + (m_{j,y} - y)^2} \\
\text{atan} 2(m_{j,x} - y, m_{j,y} - x) - \theta
\end{pmatrix} + N \left( 0, \begin{pmatrix}
\sigma_x & 0 & 0 \\
0 & \sigma_\phi & 0 \\
0 & 0 & \sigma_s
\end{pmatrix} \right) \tag{3}
\]

The \( x, y, \) and \( \theta \) denote the robot position and pose, \( i \) is the index of an individual landmark observation in \( z \), and \( j \) is the index of the observed landmark at time \( t \). Then, the desired robot pose and the measured variables of landmarks are finally determined:

\[
\begin{pmatrix}
\bar{\mu}_{j,x} \\
\bar{\mu}_{j,y} \\
\bar{\mu}_{j,z}
\end{pmatrix} = \begin{pmatrix}
\bar{\mu}_{r,x} \\
\bar{\mu}_{r,y} \\
s_t r_t \sin (\phi_t + \bar{\mu}_{r,\phi})
\end{pmatrix} + \begin{pmatrix}
\bar{\mu}_{r,\phi} \cos (\phi_t + \bar{\mu}_{r,\phi}) \\
\bar{\mu}_{r,\phi} \sin (\phi_t + \bar{\mu}_{r,\phi}) \\
0
\end{pmatrix} \tag{4}
\]

The vector \( (\bar{\mu}_{j,x}, \bar{\mu}_{j,y}, \bar{\mu}_{j,z})^T \) is the landmark estimates with the expected position. This expected position is derived from the expected robot pose and the measurement variables for this landmark. Then the environment map is constructed by the collection of these landmark vectors.

4. Experimental Verifications
Based on the consistent EKF algorithm for simultaneous localization and map estimation, we can model the surrounding scenes. First, we test our algorithm on KITTI dataset.

![Figure 2 The results of consistent EKF algorithm on KITTI dataset](image-url)
As can be seen from the figure, the robot can be located and the surrounding scenes can be modeled simultaneously by the algorithm. The point cloud part is the surrounding scene part, while the colored points connected by lines are the robot's own positioning information. In addition, we used the same algorithm to model the road tunnel scene. The sensor uses vylodyne16-line lidar, and the modeling effect is shown in the Figure 3:

Figure 3 The results of consistent EKF mapping method in road tunnel environment

It can be seen that this method can be used to model road tunnels.

5. Conclusion
Through the method of this paper, a series of sensors carried by the road tunnel inspection robot can be used to inspect the road tunnel, thus reducing the problems of low efficiency and missed inspection caused by personnel inspection. In addition, through the modeling method based on laser sensor point cloud proposed in this paper, road tunnel modeling can be realized. In the next step, precision analysis will be carried out on the modeling scene of laser point cloud in order to reach or exceed the vision detection scheme.

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