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Data Extraction of Tunnel Point Clouds from Images Captured by Robotic Camera

Introduction

The inspection and maintenance of underground tunnels are critical to ensuring their long-term safety and stability, as well as to preventing potential accidents and costly repairs. In recent years, there has been increasing interest in the use of automated tunnel inspection systems to monitor tunnel conditions and detect any signs of deterioration. These systems, developed under projects like ROBO-SPECT [1], represent a significant advancement over traditional inspection methods such as LIDAR detection and handheld camera photography.

Unlike these traditional methods, a robot-mounted HD camera offers a more efficient and effective solution for acquiring high-quality image-based data for tunnel inspection[2]. By mounting an HD camera on a robotic platform, it is possible to obtain a detailed and accurate 3D model of the tunnel environment, which can be used for further analysis and inspection.

Moreover, the integration of cross-disciplinary datasets, particularly in the areas of geometry analysis and machine learning-based data extraction, is continuing to improve the accuracy and efficiency of automated tunnel inspection systems [3]. By leveraging the latest advances in machine learning and data analysis techniques [4], it is possible to extract valuable insights from the collected data, such as the identification of cracks, spalls, and other forms of tunnel deterioration.

In summary, the use of robot-mounted HD cameras and cross-disciplinary data analysis techniques offers exciting opportunities for advancing the field of automated tunnel inspection. By continuing to innovate and improve these technologies, we can help ensure the long-term safety and sustainability of underground tunnel infrastructure.

Method

The research background is the Dublin Port Tunnel, a twin-bore road tunnel located in Dublin, Ireland, which provides a direct link between the port area and the national motorway network. The tunnel is approximately 4.5 kilometers long and consists of two parallel bores, each with a diameter of 9.5 meters. The tunnel is used for the transportation of goods and vehicles, and its maintenance and inspection are crucial for ensuring the safety and efficiency of the port's operations. The inspection area is shown in Figure 1.

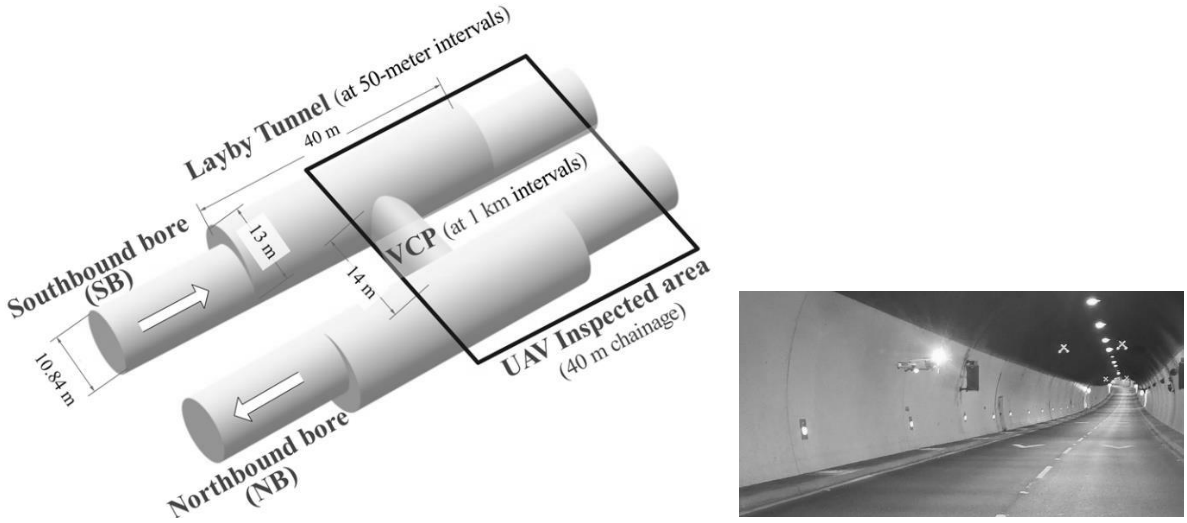
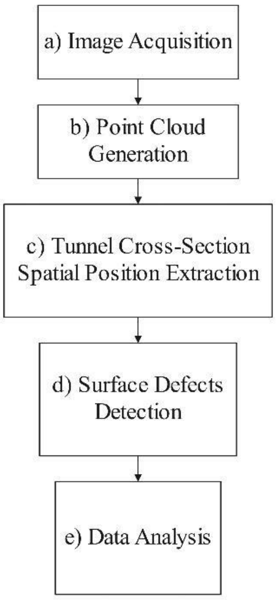


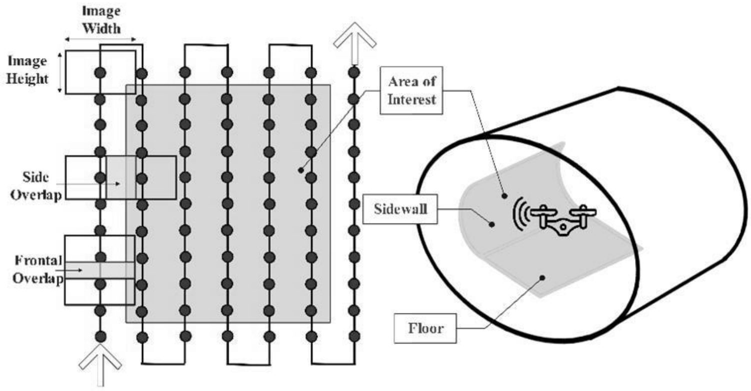
Figure 1 *Tunnel geometry and UAV tunnel inspection*

The point cloud acquisition and processing workflow

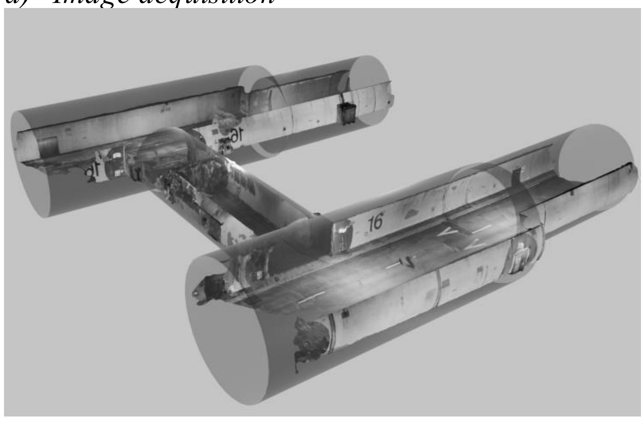
The point cloud acquisition and processing workflow indicate the engineering use for tunnel inspection. As UAV point clouds contains colour and texture information, it allows for tunnel cross-section spatial position extraction and surface defects detection at the meantime, while pure lidar point clouds only covers the former. To extract data for inspection use, we currently use a combination of data acquisition and extraction techniques in Figure 2. The following steps outline the general methodology for data extraction:

1. Image acquisition: First, high-resolution images are acquired using a UAV equipped with a high-definition camera. The images are taken at regular intervals to ensure sufficient overlap and coverage of the entire tunnel surface.
2. Point cloud generation: Using photogrammetry software Pix4Dmapper, the acquired images are processed to generate a dense point cloud of the tunnel environment. The point cloud represents a 3D model of the tunnel surface, with each point representing a 3D coordinate in space.
3. Tunnel cross-section spatial position extraction: To extract the cross-sectional spatial position of the tunnel, we can extract the cross-sectional spatial position by selecting a plane perpendicular to UAV's view and intersecting the point cloud. The resulting digital surface model (DSM) can be analysed to extract relevant features such as the tunnel diameter, cross-sectional area, and spatial position of any points on the tunnel linings.
4. Surface defects detection: surface defects can be detected using the orthomosaic image projected from a selected orthoplane. The orthomosaic image provides a 2D representation of the tunnel surface, with color and texture information. Machine learning algorithms can be trained to identify and classify surface defects such as cracks, spalls, and water leakage, based on features such as color, texture, and shape.
5. Data analysis: The extracted data can be further analyzed and visualized using various tools and techniques. For example, we can generate cross-sectional profiles, 3D models, and heatmaps to visualize the spatial distribution of surface defects and tunnel deformation.

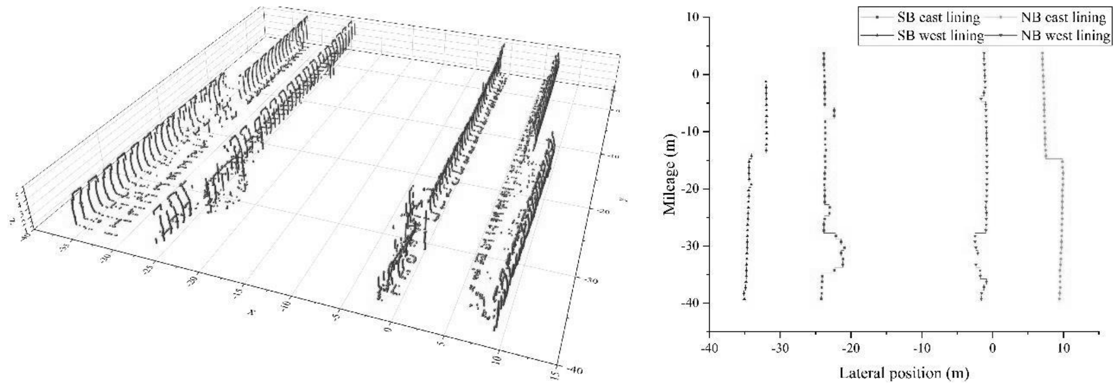




a) Image acquisition

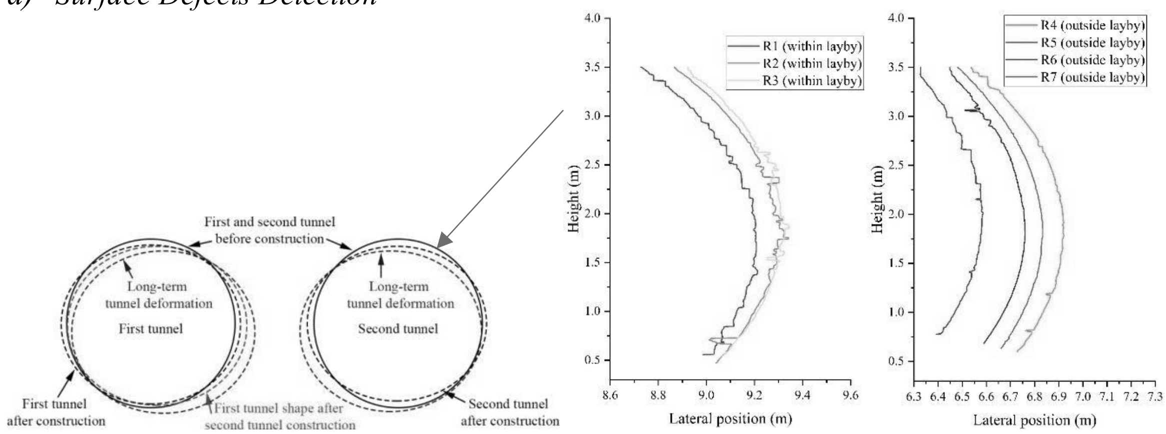


b) Point cloud generation and meshing



c) Tunnel Cross-Section Spatial Position Extraction

d) Surface Defects Detection



e) Data Analysis (verification of twin tunnel effect)

***Figure 2** Workflow of data extraction methodology with UAV point clouds for deformation and surface defects detection.*

Point cloud trimming for quality improvement

Point cloud trimming has significance in improving data quality. The geometrical point cloud trimming is the first step, which involves removing unnecessary data outside the region of interest, such as the bumps on ground surface and surrounding structures. This is typically done using geometric features of the tunnel lining, such as the extruded profile or the circular cross-section. By removing extraneous data, the point cloud becomes more manageable and the subsequent processing steps become more efficient.

The second step in point cloud trimming is machine learning-based point cloud smoothing. This step aims to remove noise and outliers from the point cloud, which can improve the accuracy of subsequent data extraction. Machine learning algorithms can be trained to identify and remove points that are unlikely to belong to the tunnel surface, based on features such as color, texture, and geometric context. The DPT meshing results has an obvious improvement after point cloud trimming, as shown in Figure 3. After the point cloud trimming, the unevenness on the rendered model is reduced.

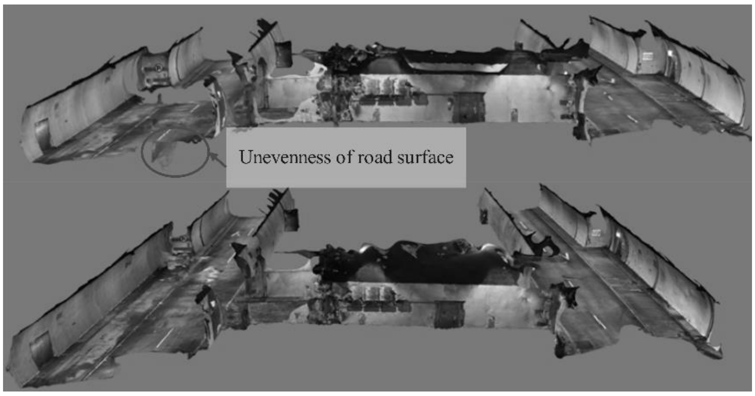


Figure 3 *Meshing results comparsion (1) before and (2) after point cloud trimming.*

Conclusions
The use of UAVs for tunnel inspection offers several advantages over traditional inspection methods, including the ability to capture high-resolution colour and texture information, which can improve the accuracy and reliability of data extraction. By using machine learning algorithms for point cloud smoothing and surface defect detection, it is possible to automate and streamline the inspection process, reducing the need for manual inspection and increasing the efficiency and safety of tunnel maintenance.

Acknowledgements
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