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Monitoring tunnel deformations by means of multi-epoch dispersed 3D LiDAR point clouds: An improved approach

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ABSTRACT

Monitoring tunnel deformations is a crucial task when evaluating tunnel stability and safety. This task requires an accurate and high-resolution spatial technique to precisely capture the meticulous anomalies on a tunnel surface. As a response, the light detection and ranging (LiDAR) technique, which collects detailed spatial data in a fast and automatic manner, was recently proposed by Han et al. (2013) for monitoring the deformation of a 2D tunnel profile. Although the proposed approach successfully uses this modern spatial technique in tunnel analysis, the benefits of the 3D LiDAR technique have not been fully exposed. This study improved the technique as a real 3D approach. The associated uncertainties can be reduced by avoiding the 3D to 2D profile projection step. The minimum-distance projection (MDP) was then estimated using directly the 3D dispersed point clouds so that any deformation signal (point displacement) along the entire tunnel surface can be immediately identified. Furthermore, a rigorous covariance propagation approach was introduced to provide explicit quality indications on the obtained solution. The results of simulation tests and a real case study of a highway tunnel showed that the spatial implications of the 3D LiDAR technique can be fully explored by implementing the improved approach. Consequently, a more accurate and comprehensive solution for monitoring tunnel deformations can be achieved.

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1. Introduction

Monitoring a tunnel profile or inner surface can provide critical insights during the lifetime of a tunnel. For example, the control of the excavation profile and the detection of undercut and overcut are required when the tunnel is under excavation, the thickness of the layer of shotcrete must be monitored during construction, and long-term monitoring task is needed for safety concerns (Gikas, 2012). Conversely, light detection and ranging (LiDAR) is an evolutionary technique that enables one to collect massive and high quality 3D spatial data in a fast and automatic manner. During recent years, various types of LiDAR scanners have been developed and used in many applications covering different fields, including topographic mapping with space-borne or air-borne LiDAR, city and transportation facility modeling with ground mobile LiDAR, and structural deformation analysis with tripod LiDAR (Petzold et al., 1999; Bretar and Chehata, 2010; Han et al., 2010; Heo et al., 2013). It is also possible to use the LiDAR technique to determine aerosol and cloud parameters in meteorological applications (Su et al., 2008; Tackett and Di Girolamo, 2009). Despite the wide variety, all LiDAR scanners work under the same basic idea that range and angular measurements are collected and used to form 3D vectors between a scanner and object points. More details about the principles of LiDAR measurements can be found in Han et al. (2013). Furthermore, the use of ground-based LiDAR for tunnel applications has recently become popular, such as excavation profile/volume control, undercut and overcut calculation, drill/blast pattern verification, shotcrete layer thickness determination, tunnel surface documentation, rock mass discontinuity characterization, and deformation monitoring (Gikas, 2012). However, a reliable algorithm that fully uses abundant spatial information in LiDAR datasets is still to be developed. Traditional deformation analysis measures displacements on the basis of a limited number of points, which is unsuitable for a global consideration of the investigated area. In contrast, LiDAR datasets, which are usually composed of millions of points, contain detailed, non-specific, and dispersive spatial information. Several studies have performed tunnel characteristics or deformation analysis using LiDAR technique (Van Gosliga et al., 2006; Vezočnik et al., 2009; Fekete et al., 2010; Nuttens et al., 2010); however, most methods must fit the tunnel to a typical geometric shape model (e.g., circular cylinder, elliptic cylinder, or a more complex model that follows the ideal design plan) before analyzing the datasets. Although it is easier to conduct a deformation analysis using these parameterized models, many details (small anomalies) may be neglected during

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the modeling process. In other words, the abundant spatial implication of a LiDAR dataset has not been fully utilized, and its capability in deformation analysis tasks has not been maximized.

To improve the use of the geometric implications inherent in a LiDAR dataset, Han et al. (2013) developed a LiDAR-based approach to detect the deformation signals (positional displacements across time) for all the points on a specific tunnel profile. By using in situ control features, tunnel profiles at multiple epochs can be automatically generated and expressed in a common datum definition. Then, by applying a minimum-distance projection (MDP) algorithm, point correspondences can be established, and the deformation signals along any profile of interest can be immediately identified. This method directly used the LiDAR dispersed point clouds (i.e. groups of points representing the geometry of a scanned object) to minimize the accuracy deterioration caused by the modeling/parameterization process. However, although the 3D dataset was used directly, its analysis was constrained on a 2D domain. The raw dataset must be projected onto a specified 2D plane to generate the tunnel profiles, on which the MDP deformations are estimated. This $R_3 \rightarrow R_2$ projection step can be regarded as an interpolation process. Consequently, some quality loss is unavoidable. Additionally, the current approach estimates only the deformation signals along the selected profiles. It cannot provide a realistic 3D representation of the tunnel dynamics. The advantages of using the meticulous 3D LiDAR technique have not been fully explored. Furthermore, the uncertainty of the detected MDP deformation signals is highly dependent on the quality of the input LiDAR dataset. An explicit quality indication for the deformation signals can facilitate the construction of a statistical criterion to properly identify actual deformations under the perturbation of observational noises.

To address all the above issues, this study improved the current approach. By avoiding the 3D to 2D profile projection step, associated uncertainties can be reduced. The MDP displacement was estimated using directly the 3D dispersed point clouds to identify deformation signals along the entire tunnel surface. The goal was to achieve a realistic estimation of the 3D deformation field across the entire area of analysis. Furthermore, a rigorous covariance propagation approach (which estimates the dispersion of a resulting quantity according to the dispersion of its original input) was proposed to provide a numerical measure on the uncertainty of the obtained MDP deformation signals. It was used to construct a statistical confidence interval to automatically identify significant anomalies (deformations). Finally, numerical examples based on a simulation dataset and a real case study were examined so that the benefits of implementing the proposed approach can be revealed.

2. Method of improvement

2.1. Estimation of 3D MDP deformation signals

In a tunnel deformation monitoring task, LiDAR datasets at varied epochs must first be collected. Using the LiDAR registration method proposed by Han et al. (2013), the datasets collected at various epochs and scanner locations can be easily registered into a common reference frame using multiple types of in situ control features. The original tunnel monitoring profile method uses a tunnel profile extraction approach by selecting a manually determined buffer size. An MDP algorithm is subsequently used to find the point correspondence between the deformed profile and reference profile so that deformations on the selected profiles can be estimated. It has been noticed that the buffer size must be carefully selected in order to maintain a maximal level of accuracy when 2D profiles are extracted. The compression of the 3D dataset to a 2D profile was conducted to simplify the problem at the expense of reality. Conversely, because the LiDAR dataset provides an original 3D representation of the scanned object, the optimal strategy is to analyze it without the $R_3 \rightarrow R_2$ projection process. In other words, the deformation signals must be estimated on a 3D surface-to-surface basis instead of a 2D profile-to-profile basis.

Fig. 1 depicts the points on a reference and deformed tunnel surfaces. It shows a typical case in which, although two surfaces belong to the same tunnel, no explicit point correspondence occurs between them. Consequently, the deformation signal cannot be accurately identified. To establish point correspondence between the points on the reference (non-deformed) and deformed surfaces, the MDP algorithm was used to find the point correspondence directly from the 3D datasets. First, a point k on the deformed surface was selected. Its distance to all points on the reference surface was computed to identify the three points (k'_1, k'_2, and k'_3) that were at a minimal distance, second minimal distance, and third minimal distance from point k. The correspondence point of point k on the reference surface was subsequently estimated by its projection on the plane formed by the three points (k'_1, k'_2, k'_3). The coordinates of this projected point k' can be then computed using the following equations:

$$x_{k'} = x_k - \frac{a^*(ax_k + by_k + cz_k + d)}{a^2 + b^2 + c^2} \tag{1}$$

$$y_{k'} = y_k - \frac{b^*(ax_k + by_k + cz_k + d)}{a^2 + b^2 + c^2} \tag{2}$$

$$z_{k'} = z_k - \frac{c^*(ax_k + by_k + cz_k + d)}{a^2 + b^2 + c^2} \tag{3}$$

where $\vec{x}_k = \{x_k, y_k, z_k\}$ and $\vec{x}_{k'} = \{x_{k'}, y_{k'}, z_{k'}\}$ denote the coordinates of point k on the deformed surface and the reference surface, respectively. $\{a, b, c, d\}$ are the parameters for the plane formed by the three points k'_1, k'_2, k'_3, which can be written explicitly as

$$\vec{n} = \{a, b, c\} = (\vec{x}_{k'_2} - \vec{x}_{k'_1}) \times (\vec{x}_{k'_3} - \vec{x}_{k'_1}) \tag{4}$$

$$d = -\vec{n} \cdot \vec{x}_{k'_1} \tag{5}$$

The projected point k' on the reference surface obtained using Eqs. (1)–(3) should have a minimum distance to point k and is regarded as the most probable correspondence point of k. Finally, the MDP distance ($\| \overline{kk'} \|$) representing the spatial displacement of point k can be computed by

$$\text{MDP} = \| \vec{kk'} \| = \sqrt{(x_{k'} - x_k)^2 + (y_{k'} - y_k)^2 + (z_{k'} - z_k)^2} \tag{6}$$

By substituting Eqs. (1)–(5) into Eq. (6), the MDP can be rearranged into a more compact form, as follows:

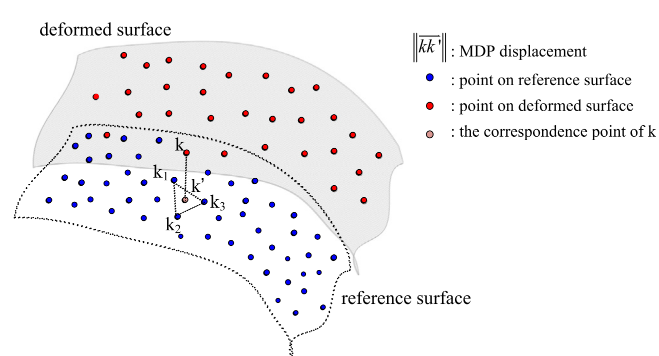

Fig. 1. MDP algorithm for detecting 3D deformations of a surface.

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