Mobile LiDAR-based convergence detection in underground tunnel environments

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Abstract

This paper presents a mobile LiDAR-based method for remotely identifying convergence (i.e., naturally occurring deformation) in excavated underground tunnel environments. A mobile LiDAR system is used to collect and generate two independent 3D point clouds of the excavated environment. In the absence of actual convergence, simulated deformation is applied to one of the two point clouds based on a simple convergence model. Registration of the 3D data is performed by using a rough alignment based on principal components, followed by a piecewise iterative closest point (ICP) algorithm. The residual point-to-surface distances are then used as a deformation signal, which is filtered using a modal analysis based on expected deformation shapes as well as a median filter. It was found that convergence deformations of 0.05 m could be confidently identified and deformations as low as 0.0125 m could be detected within residual deformation data with a mean absolute error of approximately 0.0235 m. The proposed technique therefore allows deformations on the same order as background noise to be characterized and flagged for further inspection by mine operators.

Keywords: convergence, LiDAR, frequency analysis, signal processing

1. Introduction

Underground tunnels, shafts, and drifts are subject to enormous stresses caused by the loads distributed in the surrounding rock. The stress field around these excavated openings leads to inelastic deformation that causes them to slowly close—a phenomenon known as convergence. Measuring and understanding convergence is important to geoscientists and engineers who operate in underground tunnel environments. Convergence in underground mining is a particularly serious concern, causing damage to equipment and infrastructure, project delays and production losses, as well as posing a significant risk to human safety.

Typical convergence monitoring involves the use of instrumentation installed at strategic locations for directly measuring displacement or strain. Instruments called telltales are often installed inside drilled holes, with one end anchored and the other end protruding outwards with a colour-coded indicator [1]. These mechanical devices show the amount of movement of the anchored point with respect to the rock face. Electronic telltales can be used to provide a linked network that continuously monitors deformation throughout the mine. Various types of extensometers are also available for monitoring deformation between the floor and back or between walls. Using a tape or telescopic rod and a position sensor such as a linear variable displacement transducer, extensometers can provide precise measurements on location or remotely [2, 3]. Monitoring systems based on computer vision have also been developed and tested. These typically use a digital camera to track the movement of a reflective target plate [4, 5]. Another method for measuring deformation in underground environments is the use of photogrammetry, where a 3D model is generated from 2D photographic data and used to estimate volume changes [6].

1.1. Background

The current state-of-the-art in underground surveying and mapping is the use of stationary laser...
range measurement systems based on light detection and ranging technology (LiDAR), which has become an invaluable tool for many applications in mining and geotechnics [7, 8, 9, 10]. Previous work has demonstrated the feasibility of detecting changes based on comparisons of LiDAR scans captured before and after deformation has occurred. The simplest method for detecting deformation is to compute the distance between nearest corresponding points in each scan (Hausdorff distance) [11, 12, 13]. Another approach is the use of minimum-distance projection to compare subsequent scan data and determine local deformations [14]. An improvement on the point-to-point method is to generate meshed surfaces from scan data and compute surface-to-surface distances to detect changes [15, 16]. Deformations in circular tunnel cross-sections have been analyzed by fitting ellipses to scan data and comparing the change in shape [17]. Deformation in tunnels has also been investigated by comparing LiDAR scan data to previously surveyed models [18, 19]. In many cases, alignment and registration of scan data depends on the use of designated control points that are often carefully surveyed within a known coordinate system [20, 21]. It is important to note that stationary LiDAR scanning is typically laborious and time-consuming, and often requires that operations be ceased in the vicinity of the survey.

1.2. About this Paper

This paper presents a method for remote convergence detection that uses relatively low-cost LiDAR devices mounted on a mobile platform (e.g., a vehicle), which is used to repeatedly scan areas of interest. The approach presented in this paper builds on recent advances in the field of simultaneous localization and mapping (SLAM), where LiDAR and inertial measurement unit (IMU) data are fused in order to estimate sensor motion and create 3D point clouds of underground environments where a global positioning system (GPS) is unavailable. Compared with the use of stationary LiDAR surveys, this method is prone to larger errors and higher uncertainty, but can provide acceptable results in significantly less time. In this research, two LiDAR scans of the same underground mine environment were generated from a mobile platform and used to study a method for convergence detection. Although actual convergence deformation from two time-separated scans would be preferable, simulated deformation was added to one scan due to constraints on data collection and the unavailability of reference measurements. The use of simulated deformation also provided ground-truth for evaluating the accuracy of the convergence detection algorithm.

The results presented in this paper were derived from data collected using the uGPS Rapid Mapper™ (RM) system—see Fig. 1—although any similar system could have been used. It consists of two orthogonally-mounted 2D LiDAR devices and an IMU. The device is vehicle-mounted and collects data that is subsequently processed to form a 3D map of the environment. Surveyed markers are also used intermittently to affix the map within a global coordinate frame and reduce uncertainty [22]. Fig. 2 shows an example of two point clouds covering the same region in an underground mine, generated using the RM system.

Point cloud data generated from a mobile LiDAR platform has been successfully used to generate as-built models of tunnel environments [23]. Furthermore, change detection in mobile LiDAR data has also been studied previously, demonstrating detection of changes in features as small as 20 cm [24]. The primary challenge when analyzing mobile LiDAR data to detect convergence is the high level of uncertainty associated with the reconstructed point cloud data (typically on the same or greater order of magnitude).
magnitude as the expected convergence deformation). This low signal-to-noise ratio makes direct comparison of two subsequent data sets impractical. In addition, drift due to imperfect inertial navigation causes dead reckoning errors which can vary significantly between subsequent surveys. Mobile LiDAR data is also much more sparse compared to stationary LiDAR data, resulting in less detail. Therefore, more sophisticated signal processing techniques are required to confidently detect convergence in mobile LiDAR scans. Although error and uncertainty in stationary LiDAR data has been studied [25] and may be included as part of an analysis of mobile LiDAR data, the specific variances of the reconstructed RM data were unavailable for this study.

Before analyzing the data to characterize deformation, the two data sets must be registered to minimize errors due to sensor drift. This process is achieved by using a piecewise version of the point-to-plane iterative closest point (ICP) algorithm [26]. The out-of-plane distances that remain when comparing the registered data sets are then assumed to be the measured deformation along with a large amount of noise. The measured deformation is then analyzed to determine lowfrequency responses represented by expected convergence deformation modes, and the resulting responses smoothed with a median filter to further reduce noise. The experiments reported by this paper found that deformations of 50 mm were confidently identified by using a LiDAR-based mobile mapping system such as the RM system employed here, but that deformations as low as 12.5 mm may be detectable.

2. Data, Modelling, and Simulation

Convergence is complex and non-uniform due to the stress field in the surrounding rock structure, and displacement of a tunnel face occurs generally in any direction. However, a simplified model was adopted for this study, where displacement was assumed to occur only in the out-of-plane direction (i.e., displacement along the tunnel or around its perimeter was ignored).

2.1. Data Structure

The RM system generates a point cloud by estimating the sensor pose using a combination of horizontal scan matching and inertial navigation, and transforming laser range measurements into an inertial reference frame (see [22] for further details). Data from an additional vertically-installed scanner is used to generate a 3D point cloud. The employed SICK LMS 111 laser scanner measures range at 541 points as it sweeps across an angular window of 270°, with position and orientation of the sensor estimated at a rate of 10 Hz, for a total of 5410 points per second.

A dataset is therefore composed of a series of scan slices with points defined in a Cartesian inertial reference frame. The data may also be represented in a quasi-cylindrical coordinate system where the laser range and angle form the polar coordinates, but the linear axis is replaced with an axis that follows the sensor path (defined by scan slice index, j). Out-of-plane displacement is provided as a result of the piecewise ICP registration process, but convergence deformation is reduced to displacement in the radial direction with respect to the tunnel centroid at each scan slice.

2.2. Convergence Model

The amplitude of deformation at each point in a dataset is defined by a scalar displacement map, δ. Each point is then displaced in the corresponding radial direction by the appropriately indexed value of the displacement map.

The RM system is usually mounted on the rear hitch of a vehicle, thus the scan reference frame is near to the floor. It is preferable that radial displacement be defined with respect to the centroid of the drift crosssection, otherwise displacement maps appear skewed. Therefore, the polar coordinates of the laser data are redefined with respect to the centroid. Fig. 3 shows the original and redefined coordinate systems for a single scan slice. For the i-th point, pi, in the j-th scan with centroid, ĝpi, the redefined radial direction is...
is given by \( u_i \). The scan angle is also redefined as \( \theta_i \), based on the radial direction vector and local horizon.

Modal shape functions are then used to model convergence deformation. These mode shapes are defined as a function of the laser scan angle with respect to the scan slice centroid. Two deformation modes were used for this study: 1) a uniform mode, and 2) a squeezing mode. Modes are then combined to form more complex overall deformation distributions. This approach for modelling deformation in underground tunnels has previously been used for analytical and numerical studies [27].

Fig. 4 shows the deformation modes applied to a circular drift cross-section and a sample crosssection from an RM dataset.

The uniform mode applies constant deformation, resulting in a modal function, \( \eta_1 \), that is simply unity across the entire scan slice

\[
\eta_1 = 1. \tag{1}
\]

The squeezing mode applies inward deformation to the floor and back and outward deformation to the walls. This was achieved by using a cosine modal function

\[
\eta_2 = \cos 2 \theta_i. \tag{2}
\]

Equation 3 defines the total modal displacement for a single scan slice where \( \psi_{j,k} \) is the amplitude of the \( k \)-th mode over the \( j \)-th scan slice,

\[
\delta_j = \sum_{k=1}^{M} \psi_{j,k} \eta_k. \tag{3}
\]

The total deformation across a scan slice due to the linearly combined modes with respective modal deformation magnitudes \( \psi_{j,1} \) and \( \psi_{j,2} \) is given by

\[
\delta_j = \psi_{j,1} \eta_1 + \psi_{j,2} \eta_2. \tag{4}
\]

The total deformation may also be defined as the matrix product of the modal matrix, \( H \), and modal amplitude vector, \( \psi^\top_j \), as shown in

\[
H = h\eta_1 \eta_2^\top \tag{5} \quad #
\]

\[
\psi^\top_j = \begin{bmatrix} \psi_{j,1} \\ \psi_{j,2} \end{bmatrix} \tag{6}
\]

\[
\delta_j = H \psi^\top_j. \tag{7}
\]

The modal matrix, \( H \), is the concatenation of the mode shape column vectors evaluated at the laser scan angles \( \theta_i \). Given the displacement \( \delta_j \) across a scan slice, the mode amplitudes \( \psi^\top_j \) may be determined by inverting Equation 7 using the Moore-Penrose pseudoinverse

\[
\psi^\top_j = H^\top H^{-1} H^\top \delta_j. \tag{8}
\]

The modal deformation functions apply only to the 2D drift cross-section, therefore varying the magnitudes across scan slices is necessary to achieve 3D effects. For simulation, the cross-section deformation is specified as a function of scan slice index, \( j \), using continuous sigmoid functions to define a region of constant deformation amplitude.

Convergence deformation is simulated on a RM dataset across four separate regions. The uniform and
Figure 5: Simulated convergence deformation applied to a RM dataset with radial displacement specified in metres, positive inwards. Top: applied modal amplitudes across scan slices. Bottom: radial displacement visualized over RM dataset.

squeezing modes are each applied individually over the first two regions, both modes are applied in combination over the third region, and non-modal deformation is applied over the fourth region by displacing the tunnel outwards in the lateral direction only. Figure 5 shows the applied modal amplitudes as a function of scan index number as well as the radial displacement visualized over the RM dataset. Note that smooth, continuous sigmoidal functions are used but the applied modal amplitudes vary slightly across scan indices due to the variation in scan angle with respect to the scan slice centroid.

3. Registration

Datasets generated using the RM system suffer from local errors—typically ±3 cm, based on experiments —too large to allow for direct comparison as a method for detecting convergence. In addition, repeated scans from exactly the same sensor pose is impractical. Therefore, registration of the datasets using a piecewise transformation technique is necessary to enable a proper comparison.

The registration process is composed of three phases: 1) preparation; 2) rough alignment; and, 3) piecewise transformation. The preparation phase involves manual selection and trimming of two datasets covering a common region of interest. Rough alignment then matches the centroids and principal axes of both data sets by transforming the query dataset. The fixed and roughly-aligned query datasets are then passed to an algorithm that registers sections of the query dataset within the fixed data set.

The registration method used in this paper is based on the iterative closest point (ICP) algorithm, which rigidly transforms a query point cloud to match a reference point cloud. ICP typically attempts to minimize point-to-point or point-to-surface distances between matched points in the two clouds, and many variants of the ICP algorithm have been studied.

Others have implemented non-rigid registration by using generalized methods for matching a deformed query point cloud to a reference model that accounts for significant noise, occlusions, and outlying points [28]. However, this paper is concerned with finding an appropriate non-rigid registration to remove drift in the reconstructed query point cloud while still retaining small deformations due to actual convergence. A similar problem that involves non-rigid registration of laser range data from an unmanned helicopter was investigated in [29], where drift in the motion model was compensated within the registration process.

Point cloud data from the RM system is reconstructed independently for each individual data set, therefore non-rigid registration cannot be applied based on the motion model. Instead, it is assumed that drift is negligible for small subsections of data, allowing rigid point-to-plane ICP registration to be performed for each individual scan slice based on a window of surrounding data and resulting in a piecewise rigid registration method. The transformation for each subsection is then applied only to the centre scan slice during reconstruction.

In this paper, the preparation and rough alignment phases were computed using MATLAB scripts. The piecewise transformation was computed using C++ scripts based on Point Cloud Library (PCL) functions.

3.1. Preparation

Two datasets are selected that cover an overlapping region of an underground tunnel and extracted by using the RM software. The datasets are then examined and manually trimmed to cover only the overlapping region of interest. For example, consider the two datasets shown in Figure 6, each

1 As reported at www.ugpsrapidmapper.com (March 7, 2016).
covering the same general area of an underground mine.

3.2. Rough Alignment

The centroid of each data set is computed by finding the average position of the point cloud data. Before computing the centroid, the point cloud is filtered to ensure that the point density is relatively uniform and to avoid biasing the centroid position. This is accomplished by truncating the point cloud position data based on a selected resolution and keeping only unique points, resulting in an occupancy grid data format. The same filtered point cloud is then used to determine the moment of area tensor from which the principal components of each data set are extracted. The principal axes represent the orientation of the data set reference frame within the global coordinate system. The original query data set point cloud is then transformed into the fixed data set reference frame based on the position offset and rotation. Figure 7 shows trimmed point clouds after rough alignment, resulting in an imperfect but acceptable initial registration of the two data sets.

3.3. Piecewise Registration

To obtain the results in this paper, the fixed and query data point clouds were exported from MATLAB to point cloud data (PCD) format. These files were passed to a C++ script that computed surface normals using PCL functions (based on a PCA algorithm) and performed the piecewise ICP registration for successive sections of the query data set, storing the transformations and outputting to a delimited ASCII text file.

The registration algorithm iterates through each scan slice of the query data set, sampling a window of data centred on the current query slice and registering that window of the query point cloud with a window of the fixed point cloud. The fixed point cloud window is selected based on a mapping of the nearest centroids for the bounding indices of the query data window, reducing the number of points being considered and speeding up the overall process. Margins are also added to the bounding indices to account for error remaining after rough alignment.

The point-to-plane ICP algorithm is then applied to the fixed and query point cloud windows. The query point cloud window is transformed to minimize the sum of the squared out-of-plane distances between each point in the query data and the nearest point in the fixed data (i.e., projected along the normal direction of the fixed data point). After the ICP algorithm has converged, the resulting translation and rotation transformation is stored and the algorithm continues to the next scan slice index.

Although the registration process is performed using a rigid transformation for windowed sections of the data, the solved transformation is applied only to the centre scan slice. Therefore, each scan slice is transformed independently but based on registration of a surrounding window of data, resulting in a nonrigid transformation of the overall point cloud. For the results in this paper, a C++ script outputs a delimited ASCII text file containing the translation and rotation data for each scan slice. Final reconstruction of the query point cloud was performed by using a MATLAB script.
Figure 8 shows the results of piecewise registration of the previously rough aligned query data set. Comparison of Figure 7 and Figure 8 demonstrates noticeable improvement in the alignment of the two datasets. Table 1 presents the mean, median, and standard deviation of the absolute out-of-plane distances after rough alignment and after non-rigid ICP alignment. Note that the registration results are presented for the case with no convergence deformation added, therefore the residual out-of-plane distances are strictly the result of errors due to sensor uncertainty, point cloud reconstruction, and registration.

Table 1: Point-to-plane distance statistics after rough alignment and piecewise non-rigid registration.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Rough (m)</th>
<th>Piece-wise (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.6398</td>
<td>0.0211</td>
</tr>
<tr>
<td>Median</td>
<td>0.3461</td>
<td>0.0144</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.7723</td>
<td>0.0235</td>
</tr>
</tbody>
</table>

4. Post Processing & Analysis

The residual point-to-plane distances after piecewise registration represent the deformation of the tunnel and are output as a measured displacement map to be post-processed. However, significant noise corrupts the displacement map due to the presence of measurement uncertainty during data collection, registration errors during generation of the RM data set, and registration errors during the rough alignment and piecewise registration processes. The amplitude of the noise in the displacement signal is within the same order of magnitude as the amplitude of expected convergence deformation. Therefore, inspection of the raw displacement map is not sufficient for identifying regions undergoing convergence, and post-processing is necessary to suppress noise and highlight convergence deformation.

Noise in the displacement map is randomly distributed across each point and characterized by high spatial frequencies, whereas convergence deformation is modeled using mode shapes that are characterized by low spatial frequencies. The mode amplitudes for each scan slice were determined from the displacement map by applying the inverse transformation given by Equation 8. These mode amplitudes were then further reduced to a single value at each scan slice by evaluating the norm of the mode amplitude vector

\[
\psi = |\psi|^2
\]

Mode analysis is applied to each scan slice individually (i.e., around the circumference of the tunnel) but does not suppress noise along the tunnel. A median filter with a window of 81 scan slices is therefore applied along the tunnel to further reduce noise in the mode amplitude norm signal.

Although mine operators may be interested in inspecting the individual mode responses or even the raw displacement map, the filtered mode amplitude norm, \(\psi\), provides a single scalar value at each scan slice that indicates the estimated amount of convergence deformation present.

The overall process of rough alignment, piecewise non-rigid registration, and post-processing is summarized in the flow chart shown in Figure 9.

Figure 9: Flow chart describing the overall algorithm.

5. Results & Discussion

Registration and post-processing were performed for the pair of real RM datasets shown in Figure 2 with simulated convergence deformation of various amplitudes applied to the query dataset prior to registration. Real data with actual convergence deformation was not available, therefore simulated convergence deformation was necessary and also provided a known ground truth for comparison. Based on discussions with practitioners, the desired minimum observable deformation magnitude was 0.05 m. This is the amount of deformation that should
evoke action such as detailed inspection or structural reinforcement. The analyses were also performed without any deformation applied in order to provide a baseline comparison. Although this would not be possible with real convergence deformation, it allows the combined error due to sensor uncertainty, original data reconstruction, and registration to be evaluated independently of applied deformation.

Analyses were performed using the simulated convergence deformation model shown in Figure 5 with mode amplitudes corresponding to convergence deformation of 0.05 m, 0.0375 m, 0.025 m, and 0.0125 m. The deformed query dataset was then registered to the fixed dataset and the resulting displacement map was analyzed to determine the medial-filtered norm of the mode amplitudes.

Figure 10 shows the absolute value of the displacement maps for the applied deformation, the results after registration with no applied deformation, and the results after registration with 0.05 m applied deformation. It can be seen that there are regions with relatively high residual error even with no applied deformation (most notably around scan slice 1100). These regions of high residual error represent false positives that may be interpreted as convergence deformation when in fact they are the result of error accumulated during the original data reconstruction and piecewise registration processes. The results after registration of the data with 0.05 m applied deformation show identifiable regions of convergence but there exists relatively large amounts of noise in the surrounding regions without any actual applied deformation.

Inverse modal analysis of the displacement map based on the use of Equation 8 yields the results shown in Figure 11. The mode amplitude response for both uniform and squeezing modes is still corrupted by a significant amount of noise, but shows a better correspondence with the applied mode amplitudes.

Figure 11 shows the results after taking the norm of the mode amplitudes as well as with the application of the median filter. It can be seen that the resulting response after application of the median filter successfully suppresses noise and more closely matches the applied deformation.

Figure 12 shows the norm of mode amplitudes for results with various magnitudes of applied deformation after applying the median filter, along with the norm of mode amplitudes for the actual applied deformation. The results for the case with no applied deformation are also included for comparison. Each response underestimates the convergence deformation but the overall result is that regions of convergence are clearly discernible after computing the norm of the modal response and applying the median filter.

Using the approach presented in this paper, target convergence deformations of 0.05 m are apparent to an operator but deformations as low as 0.0125 m may also be detected. This is emphasized in Figures 13 and 14 where the median-filtered norm of mode amplitudes and the unprocessed displacement map are each mapped onto the meshed surface of the scan data and compared side-by-side for applied deformations of 0.05 m and 0.0125 m respectively.

While the majority of background noise is eliminated using the proposed post-processing technique, there remain some areas of high residual point-toplane distance that could be falsely identified as convergence. The primary source of these false positives are errors in the registration process, especially at intersections in tunnels where the LiDAR sensors are exposed to open spaces causing lower point density and higher reconstruction errors. Another major source of error is due to the ICP registration method, which attempts to minimize the sum of the square of
Figure 10: Top: displacement map corresponding to simulated convergence deformation with 0.05 m amplitude. Middle: displacement map after registration of fixed and query data sets with no applied deformation. Bottom: displacement map after registration of fixed and query data sets with 0.05 m applied deformation. Note that absolute displacement is shown.

Figure 11: Top: response of each mode compared to applied deformation. Bottom: norm of mode amplitudes with and without median filter compared to applied deformation. Note these results are for the case with 0.05 m convergence deformation.

Figure 12: Norm of mode amplitudes after application of the median filter for various amplitudes of applied deformation compared to actual applied deformations.
Figure 13: Comparison of unprocessed displacement map and computed mode amplitude norm response mapped onto meshed scan data (0.05 m convergence deformation). Left: unprocessed displacement map. Right: norm of mode amplitudes with median filter applied.

Figure 14: Comparison of unprocessed displacement map and computed mode amplitude norm response mapped onto meshed scan data (0.0125 m convergence deformation). Left: unprocessed displacement map. Right: norm of mode amplitudes with median filter applied.

the point-to-plane distances based on rigid transformation of the data window being considered. Ideal registration of a deformed data set would result in zero point-to-plane residual distances at non-deformed areas, whereas the ICP algorithm spreads the residual error across all points in the windowed section. Therefore, point-to-plane distances after registration are expected to be lower than the applied
deformation and result in an underestimation of the mode amplitudes.

6. Conclusion

The techniques described in this paper demonstrate that relatively small deformations due to convergence in underground tunnels may be efficiently identified by comparison of subsequent LiDAR data sets captured on a mobile platform. Although the error and uncertainty in the measured point cloud data is on the same order of magnitude as the deformation amplitude, postprocessing techniques were successful in identifying deformation signals. By modelling convergence deformation using expected mode shapes and applying a median filter to the resulting responses, noise was successfully suppressed and the target deformation amplitude of 0.05 m was apparent. In addition, convergence deformations as low as 0.0125 m may be detectable although with higher risk of falsely characterizing residual errors as convergence.

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