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How to Find Geometric Changes in Laser Scanning Point Clouds? A Perspective on Correspondence Definitions

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Abstract

3D point clouds generated from laser scanning techniques offer opportunities for precise and efficient reality capture with higher spatial resolution compared to traditional point-wise techniques. The consequent 3D change detection and analysis based on multitemporal point clouds have seen rapid advancements over the past two decades. In this context, numerous methods have been proposed to detect and analyze surface changes in general or specific scenarios. This paper systematically reviews and illustrates various methodologies for change analysis based on laser scanning point clouds, focusing particularly on the definitions of correspondences. These correspondences between compared point clouds are defined according to the types of changes that are expected to be detected, including surface differences, displacement vectors, and parametric changes, which result in different analytical approaches. Using bi-temporal laser scanning point clouds of a rock glacier surface, we demonstrate and evaluate the impact of different methods on quantified changes and provide suggestions for selecting appropriate methods across different application scenarios. Additionally, we highlight existing challenges and research directions for advancing change analysis using laser scanning point clouds.

1. Introduction

Traditional point-wise geodetic monitoring methods, such as leveling, total stations, and Global Navigation Satellite System (GNSS), offer high-precision deformation measurements coupled with rigorous statistical analyses, benefiting from convenient acquisitions of identical points and their stochastic characteristics. Nevertheless, selecting representative measured points requires careful consideration with prior knowledge of the expected changes and often results in a sparse distribution of derived deformations (Harmening, 2020). To address these limitations, area-wise monitoring strategies were introduced, enabling the acquisition of 2D images or 3D point clouds over multiple epochs, which have been widely applied in geodesy, photogrammetry, and remote sensing. (Holst and Kuhlmann, 2016; Qin et al., 2016; Hussain et al., 2013). By recording densely distributed measurements — such as 2D pixels or 3D points — within a short time, these areal acquisition techniques provide comprehensive spatial information. Among these, 3D point clouds serve as one of the most straightforward representations of area-wise spatial data. They can be rapidly generated from laser scanning or photogrammetric techniques and further exploited to reveal the 3D dynamics of monitored objects (Qin et al., 2016; Stilla and Xu, 2023).

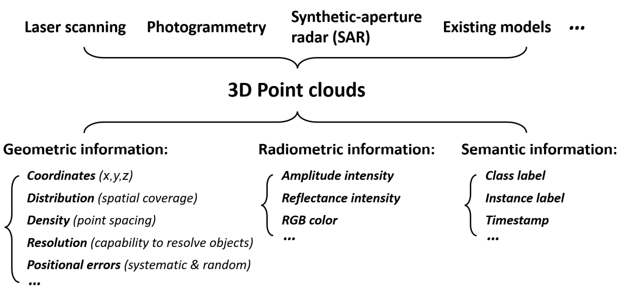

Figure 1. Typical acquisition methods of 3D point clouds and their common properties.

Figure 1 presents an overview of the current approaches to acquiring point clouds and their common properties. Point clouds collected from different sensors (e.g., cameras or laser scanners) on different platforms (e.g., tripods or vehicles) display generally similar representations but with dissimilar geometric or radiometric characteristics (e.g., point density, accuracy, reflectance, etc.) (Yang, 2023). To detect geometric changes occurring between multitemporal point clouds, theoretically, only geometric information is needed. The radiometric values can be beneficial in finding the regions or objects of interest and establishing reliable correspondences. In addition, radiometric changes can also be evaluated based on these values appended to the point cloud data. It should be emphasized that, in this paper, the changes we discuss in point clouds merely refer to the geometric changes.

In the field of geodesy, the process of detecting and quantifying these changes occurring on the monitored surface is usually formulated as "deformation analysis" (Kuhlmann et al., 2014; Holst and Kuhlmann, 2016), where the term "deformation" here, including both rigid-body movement and shape deformation (or distortion), has equivalent implications to "change" used in the geoscientific domain.

Gehrung et al. (2020) defined change as the action with semantic meanings used for object instances, deriving five major types:

- Appeared: the appearance of an object instance.
- Disappeared: the disappearance of an object instance.
- Partially moved: the movement of an object instance with overlaps in the two states.
- Fully moved: the movement of an object instance without overlaps in the two states.
- Deformed: the object instance occupies the same space during a period but changes its geometric form.

The appeared and disappeared changes are the classes usually used in *change detection*, giving a binary answer, while the similar term *deformation analysis* in the geodetic domain normally solves the problem of quantifying the change magnitudes (movements or shape deformation) of the objects that merely change within the measured scene (Gehrung et al., 2020; Lindenbergh and Pietrzyk, 2015). To facilitate the understanding and harmonize the concepts, *change analysis* is adopted herein to encapsulate change detection and deformation analysis.

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Typically, changes between two point clouds are calculated between assumed common elements which can be called *correspondences*. Since laser scanning does not measure identical points in different epochs, such as a total station does, these correspondences are usually the same artificial targets placed in the measured scenes or extracted and matched features by efficient algorithms (Lindenbergh and Pietrzyk, 2015). However, these point-wise correspondences are limited to represent the details of change events if they are relatively sparse in the scene. Besides, identical elements are hardly found in the point clouds that are fully distorted or lack artificial markers.

In the last two decades, numerous methods have been proposed and applied to analyze the possible changes in infrastructural (Kermarrec et al., 2020), industrial (Holst et al., 2019), and environmental objects (Anders et al., 2020) based on laser scanning point clouds. The accuracy and resolution of detected changes have been significantly improved by these advanced approaches. Furthermore, some general methods by comparing two point cloud surfaces enable the availability of change analysis in point clouds to more applications and scenarios (Girardeau-Montaut et al., 2005; Lague et al., 2013). Within these general methods, the change at each position is quantified on its nearest distance or the distance along specifically defined directions to the other point cloud. Since no explicit correspondences are defined in these point cloud comparison techniques, realistic changes (e.g., displacements of objects) on the surface may be underestimated (Gojcic et al., 2021). Besides, the change values calculated by different methods may show inconsistency in the same data, especially when the change directions are not well considered or the change types are not correctly assumed (Yang, 2023). Therefore, a comprehensive and accurate categorization of typical surface changes as well as change analysis methods should be clarified to adapt to different monitoring tasks and applications.

Mukupa et al. (2016) classified point cloud-based change analysis (PCCA) methods into three general categories:

- Point to point-based: calculating distances between the corresponding points in two point clouds.
- Point to surface-based: calculating distances between the points in one point cloud and the modeled surface or mesh of another point cloud.
- Surface to surface-based: calculating distances between the generated points from modeled surfaces or estimating parametric changes between the models of two point clouds.

Neuner et al. (2016) proposed five categories to systematize the methods for change (deformation) analysis from the perspective of point cloud modeling:

- Point-based: using single (identical) points.
- Point cloud-based: using partial or entire point clouds.
- Surface-based: using grid structures (e.g., mesh and voxels).
- Geometry-based: using geometric forms in the point clouds.
- Parameter-based: using parameters of approximating surfaces of the point clouds.

Stilla and Xu (2023) formulated point cloud-based change detection as a spatial difference estimation problem and listed three main types:

- Point-based: comparing spatial positions of identical points.
- Voxel- or occupancy-grid-based: comparing the occupancy states of divided grids or voxels.
- Segment- or object-based: comparing positions and shapes of segmented clusters or object instances in the point clouds.

The above three taxonomies are categorized in terms of the compared elements, and to a certain extent, there are duplications or omissions. For example, feature points may be extracted to calculate changes from two modeled surfaces by the surface-to-surface methods, which eventually return to a point-to-point approach. In the geometry-based model of the second taxonomy, the derived positions and orientations of geometric primitives (e.g., planes, spheres, cylinders, etc.) contained in two point clouds can also be regarded as estimated parameters in the parameter-based method.

Regardless of the type of changes or the methods to analyze them, it is essential to establish correspondences between two or more point clouds either explicitly or implicitly. However, when objects appear or disappear from the scene, or undergo complete shape deformation, identical corresponding elements may no longer exist. Thus, we extend the implication of correspondences within the context of PCCA, which is not limited to (assumed) identical elements. Based on varying correspondence definitions, we propose a new categorization for existing PCCA methods. The outputs of these methods are further classified into three categories: surface differences, displacement vectors, and parametric changes, which help account for the inconsistencies in the results from different approaches. For different types of changes in diverse scenarios, appropriate analytical methods should be selected to achieve accurate and meaningful change results. Therefore, this paper intends to

- — point out what needs to be considered when utilizing laser scanning point clouds for change detection and analysis,
- — define strict categories for types of geometric changes and types of results from PCCA based on a new categorization of correspondence definitions,
- — imply how to choose the most appropriate categories and processing methods to avoid misleading results.

In view of the current research state, we also analyze the existing challenges and possible solutions and outline future trends.

Section 2 provides an overview of the possible types of geometric changes in the real world and the representations of change analysis results. Section 3 proposes a new categorization of current PCCA methods from a perspective on correspondence definitions in point clouds and demonstrates the influence of different methods on change values. Section 4 and Section 5 summarize the workflow and considerations of method selection, and list the current challenges in change analysis, followed by the concluding remarks in Section 6.

2. Change Types in Reality and Results of Change Analysis

Geometric changes of real-world objects can be complex, yet we could decompose them into a variety of simpler types and regard the actual changes as a combination or hybrid of these fundamental forms. In engineering geodesy, Heunecke et al. (2013) categorized the term “deformation” (change) into rigid-body movements and distortions, assuming that the monitored objects remain in the captured scene throughout the monitoring period. The former refers to the object undergoes solely translations and rotations, and the latter means a certain level of changes in shape (i.e., shape deformation). This taxonomy facilitates the selection of suitable deformation analysis methods tailored to specific types of changes.

To integrate the change categories in the change detection problem (Gehrung et al., 2020), we redefine the types of geometric changes that may happen on object surfaces represented by measured 3D point clouds, as shown in Figure 2. Beyond rigid-body movements and shape deformation, we incorporate states of object existence, including appearance and disappearance, which cannot be expressed in terms of the former two types. Specifically, the distortion of a region can be viewed as the rigid-body movements of numerous small sub-areas within that region. Similarly, the appearance or disappearance of an object can be interpreted as movement into or out of the scene, respectively. Consequently, most object changes can be characterized as rigid-body movements, either globally or locally, which are further detailed by three translation components (t_x, t_y, t_z) and three rotation angles (R_x, R_y, R_z) (Yang, 2023).

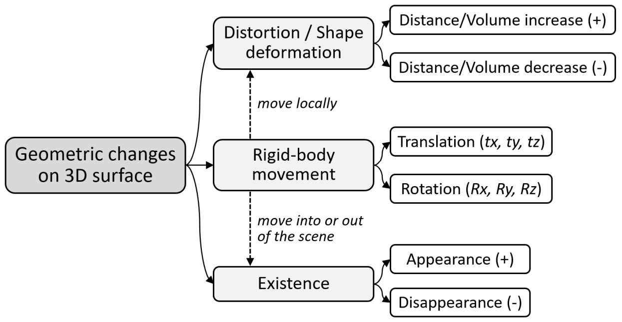

Figure 2. Types of geometric changes of monitored surface.

These real-world changes can reflect the geometric differences between point clouds and be quantified by appropriate methods. Nevertheless, each method produces a specific output format, which may not directly correspond to the types illustrated in Figure 2. Considering the existing mainstream methods and the intuitiveness and interpretability of results, we classify the PCCA outputs into three categories: surface differences, displacement vectors, and parametric changes, as listed in Figure 3.

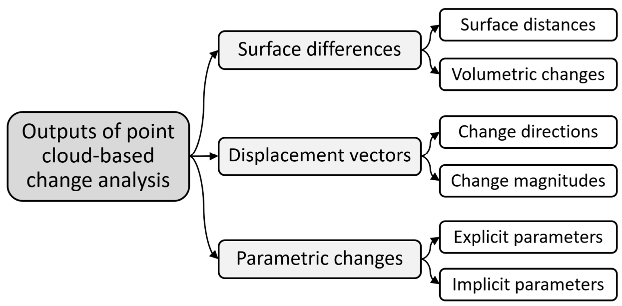

Figure 3. Types of results of point cloud-based change analysis.

The 1D surface differences can be calculated as surface distances in Euclidean space at each point or as volumetric changes within specific areas, typically visualized with a color map to represent the change values. The 2D or 3D displacement vectors provide information on both direction and magnitude of changes, offering more details than surface differences. Parametric changes involve a parameter estimation procedure that models the point cloud surface globally or locally, yielding specific parameters. These parameters, estimated over multiple epochs, may explicitly show the dimensional, positional, or postural changes of objects (e.g., the radius and center of a sphere, or the normal of a plane), or implicitly indicate the geometric changes of the surface (e.g., the coefficients of a quadric surface). The type of processing results depends on the correspondences established in the chosen strategies. The correspondence definitions and associated change analysis methods will be elaborated in Section 3.

Surface differences provide a general means of representing geometric changes through straightforward calculations. However, the realistic change directions are missing in the results, though they can be signed as positive or negative to indicate increases or decreases relative to the reference surface. Besides, movements along the surface may be underestimated or even not detected by surface differences (Gojcic et al., 2021).

Displacement vectors can reveal realistic changes as long as correct correspondences are established. Dense vectors derived by advanced algorithms can generate displacement fields for changed areas, enabling the inference about underlying dynamics. However, these vectors may not be distributed in some distorted areas where identical points cannot be found between epochs.

Parametric changes can be derived from the estimated parameters of geometric primitives (e.g., planes, cylinders, spheres, paraboloids) or constructed free-form surface models (e.g., B-spline surfaces). Accurate segmentation and surface modeling are thus crucial for detecting these changes. Certain parametric changes can be interpreted as surface differences (e.g., distances between corresponding control points on two B-spline surfaces (Harmening et al., 2021)) or as displacement vectors (e.g., the movement of a sphere’s center (Yang et al., 2021)).

3. Correspondence Definitions in Change Analysis

3.1 Correspondence Definitions and Associated Methods

As mentioned in Section 1, changes between point clouds are calculated between assumed corresponding elements. Thereby, considering the construction process of correspondences, we categorize the existing methods into five categories, as listed in Table 1, along with their principles, advantages, and limitations. Taking the closest elements as the correspondences is a straightforward and simple way that is applicable to all kinds of point clouds. The correspondence construction can be regarded as a **nearest-neighbor** search (NNS) problem in point clouds, which are commonly solved based on the *k*d-tree data structure (Bentley, 1975). For example, the nearest points or structured voxels between two point clouds are calculated as the correspondences in cloud-to-cloud (C2C) method (Girardeau-Montaut et al., 2005), and in cloud-to-mesh (C2M) or mesh-to-mesh (M2M) the closest facet (triangle) or edge in the meshed point cloud are taken as correspondences (Cignoni et al., 1998; Aspert et al., 2002). The changes calculated by NNS, however, merely represent the minimum Euclidean distance (ED) between two surfaces and may underestimate actual change magnitudes for variable topographies or in-plane movements (Yang, 2023).

The **feature-based** methods are capable of finding realistic corresponding elements, thus deriving actual displacement vectors. These algorithms are sensitive to both in-plane and out-of-plane changes. Nevertheless, the identical features between scans are still challenging to be readily extracted and matched, especially when shape deformations or non-overlapping areas occur during monitoring. Gojcic et al. (2020) proposed feature-to-feature supervoxel-based spatial smoothing (F2S3) algorithm that introduces learned 3D feature descriptors instead of handcrafted feature points and establishes correspondences in the feature space. This neural network-based technique has dramatically improved the detection and matching of features in 3D point clouds from natural scenes. However, smooth or highly deformed surfaces and the surfaces with repetitive structures are still challenging for this pipeline (Gojcic et al., 2021). Correspondence-driven plane-based M3C2 (CD-PB M3C2) proposed by Zahs et al. (2022) extracts individual planar surfaces from point clouds by region growing-based segmentation and establishes corresponding feature planes between epochs based on the plane’s parameters. The spatial distances are then calculated between corresponding planes, and thus lower uncertainties are achieved. Besides, building correspondences in converted 2D images from 3D point clouds based on feature detection in hillshade images (Hosseini et al., 2023) has also become an efficient way to derive dense displacement vectors.

The **parameter-based** methods take the same estimated parameters as correspondences. The type of derived parametric changes depends on how these parameters are defined. For example, when local normals are used as parameters, changes could be expressed as angle differences in surface orientations, whereas if parameters are the 3D positions of geometric primitives, changes may be represented as displacement vectors. The choice of estimated parameters should consider the specific

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requirements of monitoring tasks and application scenarios. Since the variances of these parameters can be derived from the adjustment process, we can directly perform significance tests on these parametric changes.

In **defined direction-based** methods, correspondences are implicitly constructed along defined directions that are assumed to align with the deformation directions. For example, the DEM of difference (DoD) method simply calculates the vertical distances of corresponding pixels of DEMs generated from point clouds (Lane et al., 2003). The standard M3C2 adopts multi-scale to estimate surface normals and treat them as the local change directions. Correspondences are then constructed by averaging the sub-clouds captured by a cylinder whose axis is along the predefined direction (Lague et al., 2013). An M3C2 variant called Patch-based M3C2 generates planar patches for the entire point clouds and projects measurements on associated patch planes, allowing lower uncertainties and better detection of small changes in complex topographies (Yang and Schwieger, 2023a). Notably, these defined direction-based methods primarily aim to quantify surface distances between point clouds. Nonetheless, the derived distance values have the potential to agree with the magnitudes of actual displacements, given appropriately defined change directions based on prior knowledge. Besides, the spatial resolution of calculated changes is not constrained compared to the limited spatial coverage of features or parameters in feature- or parameter-based methods. The deformation direction can be tailored to specific monitoring tasks or informed by prior knowledge, such as using the vertical direction when gravity is the primary deformation driver, or the radial direction when monitoring tunnel convergence (Yang and Schwieger, 2023a).

Methods	**General principles**	**Advantages**	**Limitations**	**Representative algorithms**
Nearest neighbor-based	Calculating EDs of the points in one point cloud to their nearest neighbors in another point cloud.	Simple, fast and easy to implement.	Change values are sometimes underestimated.	C2C, C2M (Cignoni et al., 1998), M2M (Aspert et al., 2002)
Feature-based	Calculating EDs of feature elements (e.g., points and planes) extracted and matched from two scans or their converted 2D images.	Real displacement vectors can be derived.	Low spatial resolution and incorrect correspondences in repetitive structures.	F2S3 (Gojcic et al., 2020), CD-PB M3C2 (Zahs et al., 2022), Image-based feature points (Hosseini et al., 2023)
Parameter-based	Calculating changes of parametric elements (e.g., normals of planes or centers of spheres) estimated by the parameterization of point cloud surfaces.	Parameters of interest and their uncertainties can be estimated.	Required prior knowledge for parameterized objects; Challenging for highly irregular surfaces.	Geometric primitives (Yang et al., 2021), B-spline surface (Harmening et al., 2021)
Defined direction-based	Calculating EDs of constructed corresponding points from two scans along defined directions (e.g., gravity direction or surface normal).	Introducing defined directions to calculate changes with high resolution.	Change values are under- or over-estimated if defined directions are unrealistic.	DoD (Lane et al., 2003), M3C2 (Lague et al., 2013), Patch-based M3C2 (Yang and Schwieger, 2023a)
Local (rigid) registration-based	Performing a rigid registration procedure locally on selected subsets of two scans to derive the transformation matrix and displacement vectors.	Dense displacement fields can be derived without feature detection procedure.	Extracting corresponding rigid areas without prior knowledge is challenging.	Local ICP (Teza et al., 2007), Patch matching (Raffl and Holst, 2024)

Table 1. Five categories of point cloud-based change analysis methods by the correspondence definition (Yang, 2023).

In point cloud registration tasks, correspondences are also established to build identical elements and estimate the optimal transformation. Conversely, if the transformation parameters are obtained between two locally rigid areas (rigid patches), we can simply calculate the distance at any position between two patches. These distances can be regarded as realistic displacement vectors if the registration accurately matches the patches between epochs (Raffl and Holst, 2024). Hence, we categorize the **local (rigid) registration-based** methods separately, as their correspondence definitions are not exclusive. For instance, when the Iterative Closest Point (ICP) algorithm is used (Besl and McKay, 1992), correspondences are built by the nearest neighbors; alternatively, correspondences become feature-based if feature points are employed for registration (Yang et al., 2016). Regardless of the registration approach adopted, all local registration-based methods compute the transformation parameters by aligning two rigid patches, allowing for displacement vectors to be calculated at each position within these rigid areas. Consequently, the resolution of displacement vectors is unrestricted in these areas. To explain the definitions of these correspondences and their implications in 3D point clouds more clearly, an intuitive schematic diagram is presented in Figure 4.

3.2 Impact of Different Correspondence Definitions

Different correspondence definitions can yield inconsistent change magnitudes at the same location. Except for certain parametric changes — such as coefficient changes in surface

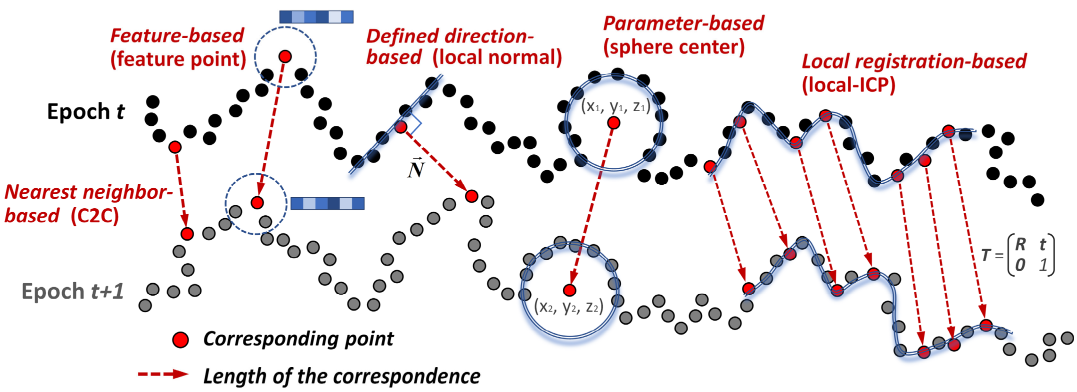


Figure 4. A schematic illustration of five types of correspondence definitions in point cloud-based change analysis.

models — that are not directly comparable to surface distances or displacement vectors, this section explores the impact of correspondence definitions within PCCA.

First, we provide a schematic comparison of distance and displacement calculations at a point, as illustrated in Figure 5. Displacement vectors represent the actual movement between corresponding elements (with explicit direction information), whereas surface distances are computed under specific criteria (e.g., between the nearest points or along a defined direction), ignoring the actual change directions. Consequently, the distance value (*Dist*) from one epoch to another may differ if the order is reversed, while the displacement magnitude (*Disp*) remains unaffected by the sequence of comparison. However, in areas with complete distortions or object appearance/disappearance, accurate displacements cannot be calculated in the absence of realistic correspondences. In such scenarios, surface distances are usually used to quantify surface changes (Yang, 2023).

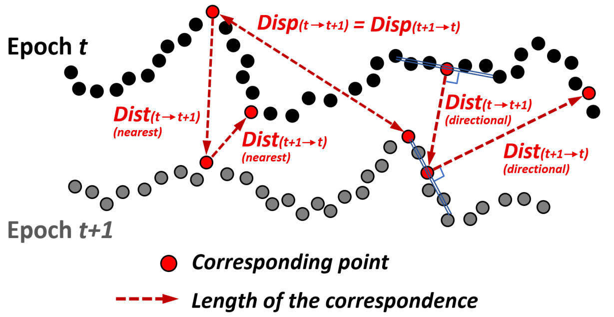
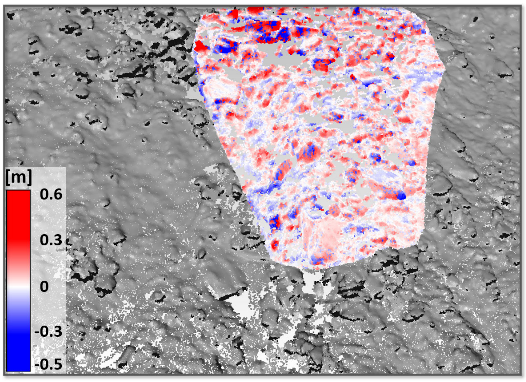


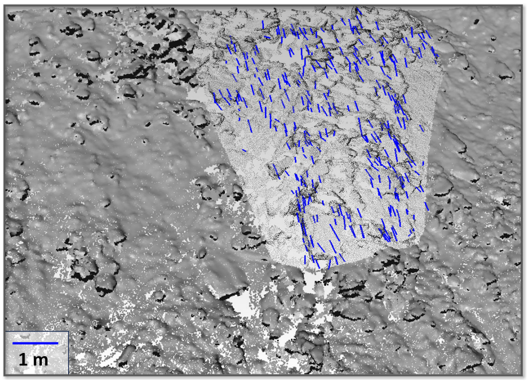
Figure 5. The difference between surface distances and real displacement vectors (Yang, 2023).

To demonstrate the differences, herein, we calculate the changes in a selected area of bi-temporal laser scanning point clouds[1] of an active rock glacier in the Alpine regions (Zahs et al., 2021). Significant changes (e.g., moving rocks and sliding debris) occurred during two measurement epochs (40 days). Figure 6 shows the calculated changes in the form of surface distance or displacement vectors obtained from four different change analysis methods, including C2M, a feature point-based method (Hosseini et al., 2023), M3C2, and local ICP (using manually selected rigid patches). Since this rock glacier surface is highly rough and irregular, lacking corresponding geometric primitives for deriving surface distances or displacements, the parameter-based approaches are not included in this result comparison. Additionally, the magnitudes of calculated surface distances or displacements are distributed in a histogram for comparative analysis, as displayed in Figure 7.

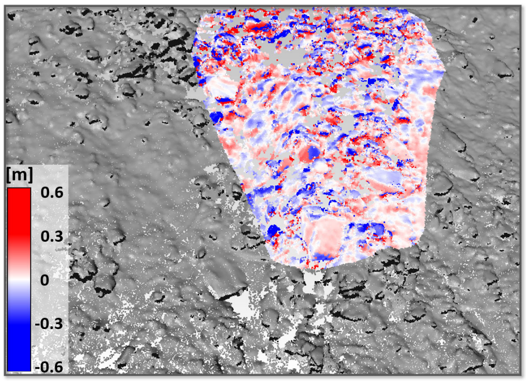
Generally, surface changes in the selected area are all detected by four methods and are well represented by surface distances or displacement vectors. However, differences regarding the directions, magnitudes, and resolution of derived changes arise due to different correspondence definitions. Specifically, feature-based and local registration-based methods can indicate 3D change directions because realistic correspondences are assumed based on correct feature matching and patch alignment. In contrast, real 3D directions cannot be derived by C2M and M3C2. However, in Figure 6, the nearest neighbor-based and defined direction-based methods produce changes with a higher resolution than the other two, particularly in some smooth or fully distorted areas. Compared to the feature point-based method, local ICP generates more displacement vectors, even in areas with fewer features (e.g., the left and right sides of the selected area). This is owing to the ability to establish correspondences at any position within the matched rigid patches.



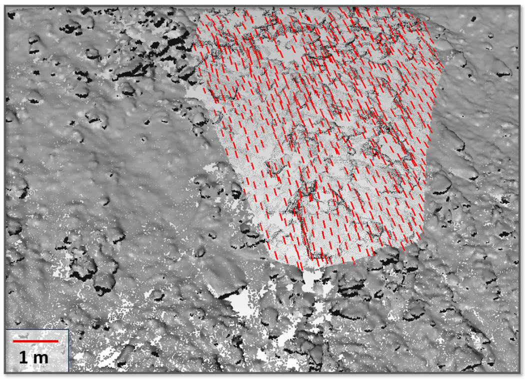
(a) Surface differences by C2M



(b) Displacement vectors by feature point matching



(c) Surface differences by M3C2



(d) Displacement vectors by local ICP

Figure 6. The geometric changes on a selected area of a rock glacier surface calculated by (a) the nearest neighbor-based method, (b) the feature-based method, (c) the defined direction-based method, and (d) the local registration-based method.

[1] The data is open source at https://doi.org/10.11588/data/TGSVUI.

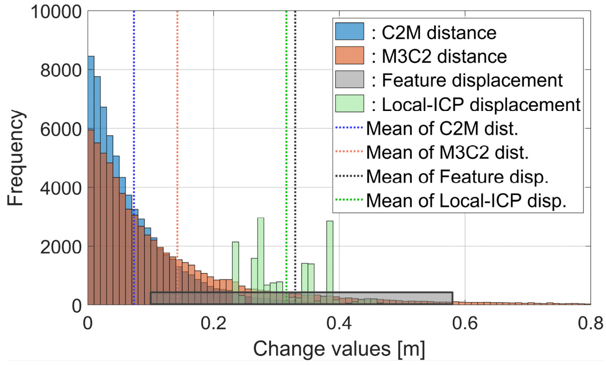


Figure 7. The histogram of change values calculated by four different methods (since the number of change values based on feature points is much smaller than the other three methods and cannot be clearly displayed in the histogram, we highlight the extent of their distribution with a gray rectangle).

Figure 7 shows the difference in change magnitudes. The mean C2M distance (7 cm) is the smallest since it calculates the nearest distance from each point to the mesh. M3C2 distances exhibit a higher mean (14 cm) because the local normals are considered to quantify surface distances. Nevertheless, both C2M and M3C2 tend to underestimate surface changes, especially when in-plane movements occurred (Gojcic et al., 2021; Yang and Schwieger, 2023a). In contrast, feature-based and local ICP-based methods report higher change magnitudes, with mean values of 33 cm and 32 cm, respectively. This discrepancy can be attributed to the fact that most changes occurred along the glacier surface, which C2M and M3C2 cannot accurately quantify. Moreover, the number of detected changes in the feature-based method is much lower than in the other three methods (387 feature points in this area), as many features are mismatched and subsequently filtered out.

This rock glacier monitoring case demonstrates that different methods with distinct correspondence definitions can lead to varying change analysis results for the same point clouds. Therefore, understanding the real-world change types, the desired form of change output, and choosing appropriate methods are prerequisites for achieving high-quality change analysis. Details of considerations and recommendations for method selection will be discussed in the following sections.

4. Method Selection for Change Analysis

4.1 General Workflow

In this section, we provide an overview of the workflow for method selection in PCCA, as illustrated in Figure 8. This workflow considers the types of real-world changes (as listed in Figure 2), the types of correspondences defined in different PCCA methods (as listed in Table 1), and the types of output results produced by each method (as listed in Figure 3). The arrows indicate potential connections among these components. For example, to detect rigid-body movements between two scans, one can extract and match feature points to establish feature-based correspondences, ultimately deriving displacement vectors. Another option is to segment and match rigid patches between scans and use local registration-based methods to generate dense displacement vectors in the rigid areas. Besides, parameter-based correspondences can be established by estimating the positions of key elements of existing (rigid) geometric primitives (e.g., the center of a sphere or vertex of a cone). Positional changes are then easily obtained by calculating the distances between corresponding parameters.

After quantifying different types of changes, their significance should be evaluated if the associated uncertainties are known or estimated from the calculation process. A common approach involves estimating an interval to determine whether the changes are significant or merely influenced by uncertainties. This interval can be defined using simple (empirical) thresholds or by performing a statistical test (e.g., t-test or F-test) by considering the variance-covariance matrix (VCM) of change values.

4.2 Considerations of Method Selection

The surface geometry and its representation by captured 3D point clouds vary widely across real-world scenarios, and there is, to the best of the author's knowledge, no universal change analysis method to cope with all cases perfectly. The complexity of change types necessitates a diverse range of relevant methods. Besides the workflow in Figure 8, selecting appropriate PCCA methods for specific scenarios should consider following aspects:

- The requirements of monitoring tasks (e.g., areas of interest, types of desired output change, the temporal and spatial resolution of represented changes, expected accuracy, etc.).
- The change process in the real world (e.g., change types, directions, magnitudes, velocity, etc.).
- The surface geometries of monitored objects (e.g., dimension, shape, surface rigidity, roughness, etc.).
- The characteristics and quality of captured point clouds (e.g., point density, spatial resolution, coverage, accuracy, etc.).

Complex scenes or tasks with specific requirements may benefit from combining different methods. For instance, a defined direction-based method can be used to detect surface differences in the deformed areas of a landslide, while the local registration-based or feature-based method might be used to calculate the movement of trees or boulders situated on the landslide. These monitored objects in the scene can be separated by point cloud classification techniques prior to conducting change analysis.

5. Current Challenges and Future Directions

In spite of the significant advancements in PCCA in recent years, several challenges and limitations still exist. This section outlines some of the key challenges in geodetic monitoring tasks.

5.1 Accurate Registration/Georeferencing

Accurate alignment between compared point clouds is the prerequisite for change analysis. For laser scans containing changed areas, only the points in stable areas can be involved in the registration process. These stable correspondences can be achieved by placing some artificial targets evenly distributed within the scanned area. However, several downsides of the target-based registration strategy are evident despite its high accuracy and reliability (Janßen et al., 2022), such as the necessity to access the monitored areas, and the instability of target positions due to possible movements of their located regions. Therefore, automatic identification of the stable areas in two unregistered point clouds plays a significant role in PCCA, especially in complex natural environments where distinguishing between stable and unstable regions manually is challenging (Wujanz et al., 2016; Yang and Schwieger, 2023b).

5.2 Estimating Systematic and Stochastic Uncertainties

Point clouds captured by laser scanners inherently contain both systematic and stochastic errors, arising from various sources such as instrumental errors (e.g., inaccurate calibration), atmospheric effects (e.g., refraction), surface properties (e.g., roughness), scanning geometries, and georeferencing errors. Incorrect change analysis may occur if these uncertainties are not adequately considered. For example, change values are inaccurately quantified due to incorporating the systematic errors

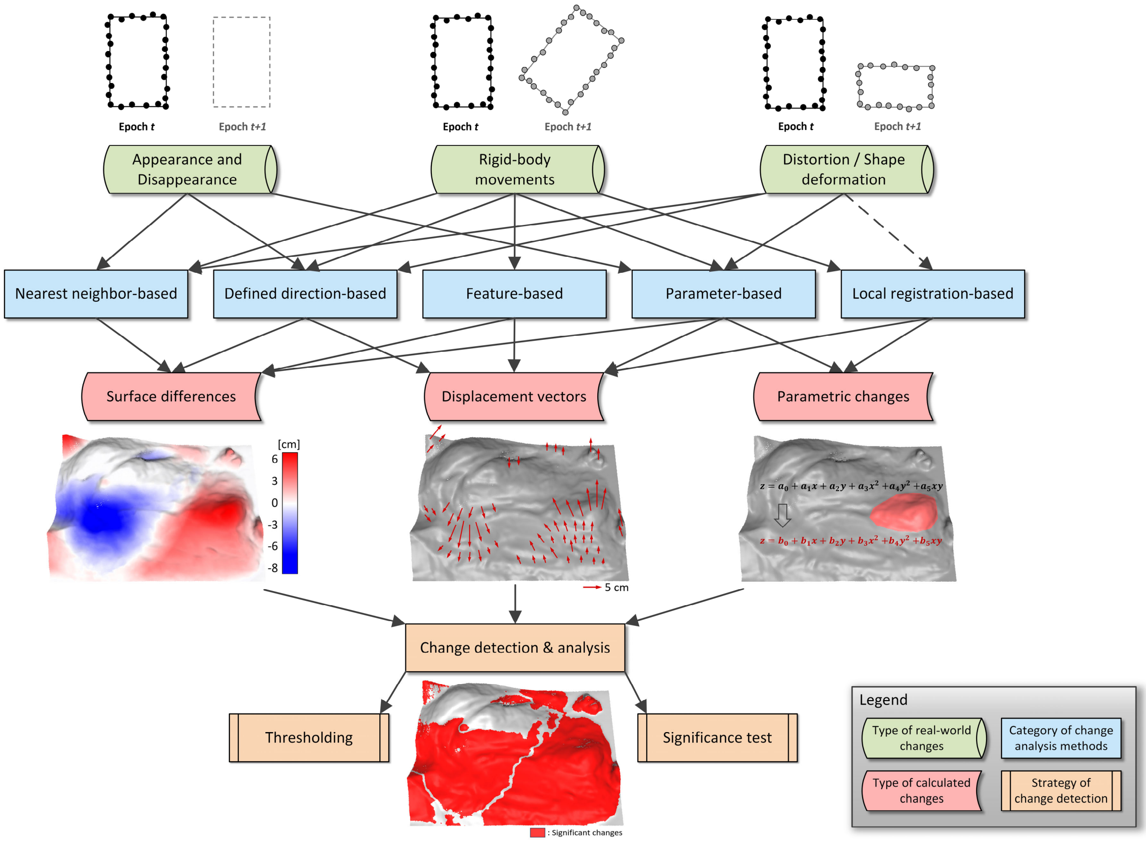


Figure 8. A workflow of method selection for point cloud-based change analysis.

from uncalibrated scanners (Holst et al., 2019), or the classical significance test reports a contrary result when the standard deviations of parameters are underestimated (Yang, 2023).
Systematic uncertainties should ideally be identified, quantified, and applied to correct observations (point clouds). However, completely isolating these systematic errors in laser scans remains challenging (Holst and Kuhlmann, 2016). In most practical cases, stochastic uncertainties of point clouds are simply estimated by using the scanner's specifications or the residuals from surface modeling. These empirical ways often yield a simple diagonal VCM, which fails to account for correlations. As a result, the estimated uncertainties may not agree with the realistic error characteristics, leading to inaccurate parameter estimation and change detection. Thus, a more realistic stochastic model should be considered by integrating a fully populated VCM for the point cloud (Kerekes and Schwieger, 2020).

5.3 Robust Identification of Features and Rigid Patches

Most methods developed for PCCA are solely based on the geometric information of point clouds. Despite their generality and applicability on point cloud data captured from various sensors, correspondences from feature points and rigid patches may not be correctly established merely relying on geometric properties (e.g., correspondences might be ambiguous in areas with repetitive structures or planar surfaces). In local registration-based methods, patches by manual and empirical segmentation (as conducted in Figure 6(d)) may not be fully rigid. The contained non-rigid parts can cause a local minimum in ICP, thereby reducing the accuracy of the derived displacements. Hence, automatically and precisely identifying the rigid patches in deformed point clouds remains a significant challenge.
For feature matching, radiometric information like RGB colors or reflectance along with the point coordinates can be exploited to enhance the descriptiveness of extracted feature points (Gojcic, 2021). A current solution introduces photogrammetric point clouds for change analysis, which builds corresponding feature points from captured RGB images (Lucks et al., 2024). Similarly, by taking both geometric and radiometric information into account for the instance segmentation, more geometric primitives and individual rigid patches can be extracted and fed into the parameter- or local registration-based methods.

5.4 Change Analysis of Point Cloud Time Series

High-temporal resolution data acquisition, like using permanent terrestrial laser scanning (PLS) system, can generate dense point cloud time series, enabling more detailed capture and analysis of continuous surface change processes. When dealing with thousands of epochs, each containing millions of points, subsequent processing requires high computational efficiency and consideration of temporal correlation, especially in real-time monitoring applications (Winiwarter et al., 2023). Furthermore, rapidly recognizing change events and their patterns in massive point cloud time series also remains challenging and is expected to be a key area of future research (Anders et al., 2020).

6. Conclusions

This paper provides a systematic overview of the methodologies to analyze geometric changes in laser scanning point clouds. Starting with the definition of real-world surface change types, we propose three kinds of output changes from PCCA: surface differences, displacement vectors, and parametric changes. From a perspective of correspondence definitions between laser scans of different epochs, we introduce a new categorization of existing PCCA methods, including nearest neighbor-based, feature-based, parameter-based, defined direction-based, and local registration-based methods. This categorization provides a comprehensive and logical framework for summarizing the principles of current techniques. Following this framework, we outline a general workflow and offer concrete suggestions for selecting the most suitable methods. The opinions and insights presented herein are based on a literature review as well as our practical experience in laser scanning-based geodetic monitoring across a variety of applications. Finally, we summarize current challenges in PCCA and provide potential solutions as the outlook for future work.

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