A ROBUST SURFACE MACTHING TECHNIQUE FOR DEM INTEGRATION IN THE CONTEXT OF COASTAL GEOHAZARD MONITORING

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ABSTRACT:

With the increasing availability of a diverse range of datasets from sources such as airborne and terrestrial laser scanning, InSAR, and high resolution satellite remote sensing, there are improved opportunities for dataset integration and the synergistic benefits which this can offer. However, accurate registration is a fundamental pre-requisite for data fusion, and an issue which is often overlooked. This paper presents a strategy for improving the effectiveness of coastal geohazard monitoring through the integration of airborne and terrestrial laser scanning datasets. This approach is based upon a robust least squares surface matching technique, which enables the reliable reconciliation of disparate datasets, overcoming disparities between the input surfaces. The development of the matching algorithm, which incorporates a robust M-estimator function, is detailed. Application of this approach to a test site located on the east coast of England highlights the effectiveness of the robust matching algorithm for data integration, improving the quality of the resultant surface models, and facilitating subsequent analysis of change over a four month period. Robust surface matching is a flexible technique, which shows significant potential for a range of data fusion tasks, particularly where there is also a requirement for reliable change detection.

1. INTRODUCTION

The last decade has seen the commercial realisation of a number of technologies, such as airborne laser scanning (lidar), terrestrial laser scanning, InSAR, and high resolution optical satellite sensors. The net effect of this is the increasing availability of a range of datasets, offering unprecedented opportunities for exploiting this wealth of geospatial data. In particular, data fusion is an area which holds much potential, and which has been the focus of significant research effort (e.g. Schenk and Csathó, 2002; Buckley and Mitchell, 2004; Dowman, 2004). However, while data integration offers synergistic benefits, this approach also presents significant challenges in terms of ensuring effective reconciliation of disparate datasets. In particular, as emphasised by Schenk and Csathó (2002), registration to a common reference frame is a fundamental prerequisite.

The coastal zone is an environment which demands effective assessment of change, and which stands to benefit from an approach structured around dataset integration. Coastal geohazards, which include processes such as landslides and rockfalls, represent a major driver for coastal change. Where these phenomena interact with the human environment, monitoring is essential for effective coastal management and planning. However, the complex nature of cliffed coastal topography means that in general, no one technique in isolation is capable of delivering an effective monitoring solution. While airborne techniques enable rapid acquisition of large tracts of coastal terrain, more vertical components of the landscape are often obscured. Conversely, while the value of a terrestrial approach increases in the vicinity of cliffs, an approach based solely on terrestrial acquisition is usually restricted to relatively limited spatial extents.

In response to these challenges, this paper presents an integrated solution to coastal geohazard monitoring, which explores the maturing techniques of airborne laser scanning (ALS) and terrestrial laser scanning (TLS). TLS is capable of facilitating assessment of localised pockets of geohazard activity, offering unrivalled spatial resolution and speed of acquisition over traditional land surveying techniques. ALS offers several complementary benefits. Firstly, in addition to enabling effective capture of areas such as beaches, ALS is also well suited to the acquisition of flatter slope elements within the cliff. Furthermore, ALS permits rapid acquisition over large spatial extents. Whereas aerial photogrammetry can be prone to image matching problems in areas of homogeneous terrain, such as beaches (Hapke and Richmond, 2000), as a direct sensing technique, ALS is capable of returning a consistent representation of the terrain.

One common challenge, of relevance to virtually all coastal monitoring approaches, is the issue of establishing reliable survey control. The coastal arena is a dynamic environment, and tidal fluctuations coupled with the presence of terrain instability have the potential to undermine the integrity of both short- and long-term control points. In order to overcome this problem, this paper presents a robust least squares surface matching solution, which facilitates the automated registration of disparate datasets. This overcomes the reliance upon physical control points, and instead derives control from the surface geometry of the datasets. Change detection is a common requirement in many natural environment applications, and an inherent advantage of least squares surface matching is its in-built capacity for detection of differences between the matching surfaces. In the application at hand, this may relate to multi-temporal geohazard activity, vegetation change, or surface discrepancies arising as a result of differing acquisition techniques. However, where such differences are extreme, least squares surface matching may fail, or the matching surface may be 'pulled' into an erroneous solution. In order to address this issue, a robust maximum-likelihood estimator (M-estimator) has been incorporated in the matching algorithm. This facilitates automated down-weighting of outlying observations corresponding to regions of difference. To date, investigation of robust surface matching in the field of geomatics has been relatively limited and largely restricted to experimental datasets. This paper presents the application of this approach to real-world laser scanning datasets in the context of coastal geohazard monitoring.

The overall aim of this research is to develop a flexible and effective strategy for coastal geohazard monitoring, which simultaneously addresses the problematic issue of dataset registration in the dynamic coastal zone. In order to achieve this, an approach based on the integration of airborne and terrestrial laser scanning datasets is proposed. A robust surface matching algorithm has been developed, which facilitates automated fusion of the multi-sensor, multi-temporal datasets, and offers an inherent capacity for change detection. The development of this algorithm is presented in the following section. The coastal monitoring methodology is then outlined, and results of multi-sensor dataset fusion are presented alongside multi-temporal change analysis. The outcomes of the research are discussed and in conclusion, key research findings are highlighted.

2. ROBUST SURFACE MATCHING

2.1 Surface Matching Overview

In the most general case, the goal of surface matching is to establish the optimal transformation which aligns or registers two free-form 3D point datasets (Besl and McKay, 1992). One surface is usually treated as the 'fixed' reference surface, while the other is regarded as the unfixed matching surface, with the objective being to register the matching surface to the reference surface. In most applications, this task is not straightforward, and through efforts to address this problem, a wide range of solutions have been proposed. One of the most familiar approaches is the Iterative Closest Point (ICP) algorithm, initially proposed by Besl and McKay (1992). In its fundamental form, the ICP algorithm is an iterative procedure which searches for pairs of closest points between two surfaces, and estimates the rigid transformation which aligns them. The recent uptake of TLS has prompted a resurgence of interest in the basic registration issue from within the geomatics community. This has been further sustained by the increased availability of multi-sensor data, which requires registration to a common reference system prior to further analysis. A wide range of solutions have been proposed, but a review of these is beyond the scope of this paper. A comprehensive overview of surface matching strategies can be found in Gruen and Akça (2005).

This paper adopts a solution which is based on least squares surface matching. Least squares matching is a well-established technique for many photogrammetric routines, and is also applicable to the surface matching problem. Ebner and Strunz (1988) and Rosenholm and Torlegård (1988) introduced least squares surface matching for the absolute orientation of photogrammetric stereo-models, utilising existing DEMs as the reference surface. This same basic approach, which relies upon least squares minimisation of vertical differences between the two surfaces (Z-minimisation), has been applied by a number of researchers since (e.g. Karras and Petsa, 1993; Mitchell and Chadwick, 1999; Mills et al., 2005).

Least squares matching is generally sufficient for matching of 2.5D surface models, presenting an effective alternative to the more intensive ICP algorithm (Mitchell and Chadwick, 1999). 2.5D DEMs currently dominate natural environment applications, and consequently, least squares matching through Z-minimisation is well-suited to the application presented here. The matching algorithm is based on the 3D conformal coordinate transformation, which provides a means of converting from one 3D coordinate system to another. This can be expressed in matrix notation as:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = s\,M \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} T_x \\ T_y \\ T_z \end{bmatrix} \tag{1}$$

Where the initial coordinates of a point, (x, y, z), are modified through application of the scale factor, s, the rotations $(\omega, \varphi, \kappa)$, as defined by the orthogonal rotation matrix, M, and the translation vector (T_x, T_y, T_z), in order to obtain the final transformed coordinates, (X, Y, Z).

The algorithm implemented in this work enables matching of TIN-based datasets in order to avoid inaccuracies introduced through interpolation to a regular grid. This approach seeks to globally minimise vertical distances between points on the matching surface and conjugate surface patches on the triangulated reference surface. This allows for recovery of the seven unknown transformation parameters – the rotations $(\omega, \varphi, \kappa)$, translations (T_x, T_y, T_z), and scale factor (s) – which relate the two surfaces through the 3D conformal coordinate transformation expressed in (1). The development of the mathematical model for least squares surface matching, implementing the Z-minimisation strategy, can be found in Rosenholm and Torlegård (1988); Karras and Petsa (1993) and Mitchell and Chadwick (1999), with minor variations, and hence will not be reiterated here.

2.2 Robust Surface Matching

2.2.1 Overview: This research has seen the extension of the least squares surface matching algorithm to incorporate a capacity for robust outlier handling. As already explained, the registration solution may become sub-optimal or erroneous if the matching surfaces contain significant regions of difference. This scenario is likely to arise in multi-temporal analysis of geohazard activity, where the occurrence of a major landslide (for example) could result in differing surface representations at different instances in time. Karras and Petsa (1993) employ a data-snooping technique in a medical application of least squares surface matching for deformation detection. However, in their findings, they note that while this approach is successful in the detection of isolated outliers, spatially correlated deformation is harder to detect (Karras and Petsa, 1993).

An alternative strategy is to incorporate robust estimation techniques within the least squares matching procedure. Through this approach, weighted least squares can be applied, with weights derived from a weighting scheme, which is defined through the choice of robust estimation function. This allows those points which produce large residual values to be down-weighted accordingly. Pilgrim (1996) implemented robust surface matching, using a modified M-estimator, for detection of simulated growths and swellings in a medical photogrammetric application, noting improved performance over the non-robust version of the algorithm. Li et al. (2001) evaluate the performance of several robust estimators, through application to simulated datasets. However, while these two studies highlight the potential of the technique, they are based on simulated datasets for close range applications. In the field of geomatics to date, little has been done to evaluate the practical implementation of this technique using real-world data. Robust surface matching is a technique which is well-suited to the automated reconciliation of disparate datasets, particularly where there is a demand for change detection. Consequently, this technique holds tremendous potential for data integration in the context of coastal geohazard monitoring.

2.2.2 Implementation: In this research, a least squares surface matching algorithm incorporating a robust function from the M-estimator family has been developed. M-estimators are a popular class of robust estimator, offering flexible performance (Goodall, 1983), and permitting straightforward inclusion in least squares procedures. The generalised form of the M-estimator can be defined as (Pilgrim, 1996):

$$\sum_{i=1}^{n} f\left(v_i\right) = \min \qquad (2)$$

Thus M-estimators attempt to minimise a function of the least squares residuals $f\left(v\right)$. Further background on M-estimators is provided by Goodall (1983) and Mirza and Boyer (1993). In this research, Tukey's Biweight was selected for application. The Biweight is one of the most commonly-utilised M-estimators, and as highlighted by Li et al. (2001) in the context of robust surface matching, offers strong robustness characteristics. The weight function for the Biweight is defined as:

$$w_b\left(u\right) = \begin{cases} \left(1-u^2\right)^2 & \left|u\right| \le 1 \\ 0 & \left|u\right| > 1 \end{cases} \qquad (3)$$

Where the Bisquare weights, w_b, are calculated as a function of the standardised least squares residuals, u. In practice, the Biweight function can be implemented through a technique known as iteratively reweighted least squares (IRLS). This involves the application of weighted least squares, which is a straightforward extension of the normal case. Through IRLS, the weight matrix is recomputed as a function of the standardised least squares residuals after each iteration (Li et al., 2001). Consequently, the weights are not held fixed, but alter in response to the fluctuating residuals. This approach provides a means of mitigating the influence of concentrated regions of difference between the matching surfaces. Such differences may arise for a number of reasons, including as a result of geohazard activity or vegetation change. In addition, the incorporation of a robust estimator also provides a mechanism for automated handling of isolated outlier observations. The robust estimation function was incorporated in the least squares surface matching algorithm as outlined above, and initial testing was carried out using artificial datasets with outlier effects induced (Miller et al., 2007). Previous work, focussing on the absolute orientation of archival photogrammetric DEMs for geohazard monitoring, has demonstrated the superiority of the robust algorithm over the non-robust version (Miller et al., in press). The remainder of this paper concentrates on the evaluation of this approach as a data integration technique, with respect to laser scanning point cloud datasets in the coastal zone.

3. DATA ACQUISITION

3.1 Test Site

The test site for this research is located at Filey Bay on the North Yorkshire coast of eastern England. This nine kilometre-long bay is fronted by a broad, flat expanse of sand, and is backed by moderately-steep cliffs, which rise to between 30 and 50 metres in height. The cliffs are largely composed of soft glacial tills, which are prone to erosion and failure. The main test area (Figure 1) is located at the southern end of the bay, and is comprised of a relatively large landslide complex.

Figure 1. Filey Bay test site.

3.2 Data Collection and Preparation

Two epochs of ALS and TLS data were acquired for the test site, in April 2005 and August 2005. Analysis of change over a summer period (April to August) allowed for the robust matching algorithm to be tested using datasets which were likely to include discrepancies due to vegetation growth, as well as the potential effects of geohazard activity. ALS data was captured by the UK Natural Environment Research Council's Airborne Research and Survey Facility (ARSF), using an Optech ALTM 3033 instrument. The data was acquired from a flying height of 1000 metres, resulting in a spatial resolution of approximately 1 point/m^2. The datasets were georeferenced through on-board GPS-IMU. The April 2005 TLS dataset was acquired using a Riegl LPM-i800HA scanner with an 800 metre range, while a Leica HDS3000 scanner, with a range of 50 m was used for the August 2005 TLS survey. TLS enabled the capture of high resolution point clouds, with point densities ranging from 20 to 80 points/m^2. Standard control approaches were employed in order to register the TLS datasets to a global coordinate system. Following data acquisition, ground classification was performed using TerraSolid's *TerraScan* software in order to remove vegetation and other non-ground effects from both the TLS and ALS point clouds.

Two parallel check profiles, spaced 60 metres apart, were measured by total station for validation purposes. These consisted of shore-normal profiles which ran from the cliff-top, down the cliff-face, and across the beach into the inter-tidal zone. Points were collected every 0.5 metres, and each profile was measured three times to ensure precision. The profiles were re-occupied for comparison during subsequent surveys.

4. RESULTS

In order to integrate the ALS and TLS datasets prior to multi-temporal change analysis, the robust surface matching algorithm outlined in Section 2 was applied. Quality analysis of the individual datasets at the check profile locations indicated that the ALS datasets were of consistently higher accuracy than the TLS datasets, with an average RMSE of 27 cm, compared to 66 cm for the TLS datasets. This is most likely due to the nature of the terrain. As Figure 1 indicates, parts of the cliff are densely vegetated. This may have prevented the TLS points from penetrating completely to the ground, resulting in a classified ground model which is slightly elevated. The oblique scanning angle of TLS is likely to have exacerbated such problems. Furthermore, the oblique scanning angle, combined with the complex slope morphology resulted in a number of data occlusions, which are likely to have further degraded the fidelity of the TLS surface model. Consequently, for both the April 2005 and August 2005 epochs, the ALS datasets were held as the fixed reference surfaces, and the TLS datasets registered to these. The scale parameter was omitted from the transformation, as no scale variations were anticipated between the datasets. This allowed for a refinement in the registration solution of the TLS data, ensuring correspondence with the ALS datasets.

The post-match integrated surfaces for the two epochs were validated using the check profile data. The results of this assessment for the April 2005 epoch are presented in Table 1. This details the vertical quality of both the pre- and post-match datasets, and highlights two key outcomes. Firstly, as indicated by the RMSE values (Table 1), the application of robust surface matching has improved the overall accuracy of the TLS dataset. Secondly, the merger of the post-match TLS dataset with the ALS surface has resulted in an integrated dataset of markedly higher quality than the TLS surface alone. Similar results were also achieved through surface matching-based integration of the August 2005 datasets.

Examination of the post-match datasets revealed that this procedure had been particularly beneficial in overcoming weaknesses in the TLS datasets, as illustrated in Figure 2. The original TLS surface model (Figure 2A) contains several occluded regions, which are manifest as weak areas in the triangulation. Surface matching and merger with the ALS dataset has enabled effective in-filling of these areas, and has also provided multi-resolution coverage (Figure 2B).

Surface	Profile	Mean (m)	σ (m)	RMSE (m)
TLS pre-match	A	0.600	0.799	0.995
	B	0.236	0.448	0.502
TLS post-match	A	0.297	0.879	0.922
	B	0.010	0.326	0.323
TLS-ALS merged	A	-0.074	0.315	0.322
	B	-0.056	0.260	0.264

Table 1. Profile validation statistics for multi-sensor matching of the April 2005 datasets.

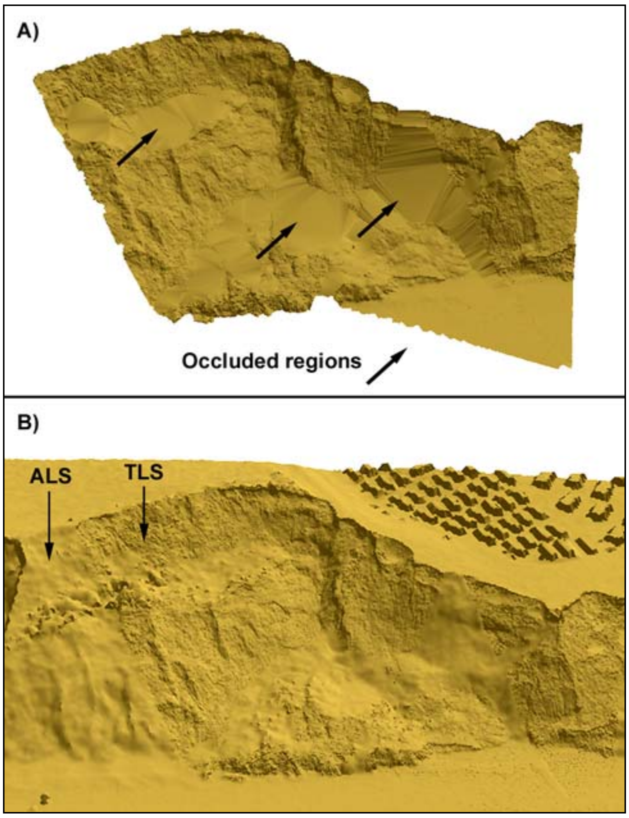

Figure 2. Occlusions in TLS dataset (A), overcome through integration with ALS data (B).

Following multi-sensor data fusion, further surface matching was carried out in order to facilitate change detection between the two epochs. Check profile analysis indicated that the August 2005 integrated DEM was of highest accuracy, and so this was selected as the fixed reference surface for matching of the April 2005 merged DEM. Post-match check profile validation confirmed that robust surface matching had succeeded in improving the accuracy of the April 2005 dataset, raising this to a level which closely conforms with the absolute accuracy of the August 2005 merged DEM.

As already stated, least squares surface matching offers an inherent capacity for change detection. The final post-match residuals correspond to vertical differences between the matching surfaces, and are output on convergence of the software. For the multi-temporal matching carried out here, the post-match residuals were analysed in a GIS in order to examine change over the period April to August 2005. The results of this procedure are presented in Figure 3, alongside an ortho-image from August 2005, acquired at the same time as the ALS dataset. Regions of difference are consistent with the effects of geohazard activity and vegetation change, suggesting that the robust matching approach has proved effective in reconciling the multi-sensor, multi-temporal datasets through refinement of the registration solutions. Figure 3 highlights a number of specific trends, including erosion affecting the cliff-face (A) and toe scarp (E); vegetation growth over the summer months (B); and notable changes to the beach level (D). Erosion within the landslide scar at C, suggests further widening of this feature. Detailed inspection of the differences indicated that the incorporation of TLS data had revealed subtle geohazard processes, which were not present through analysis of the coarser ALS datasets alone.

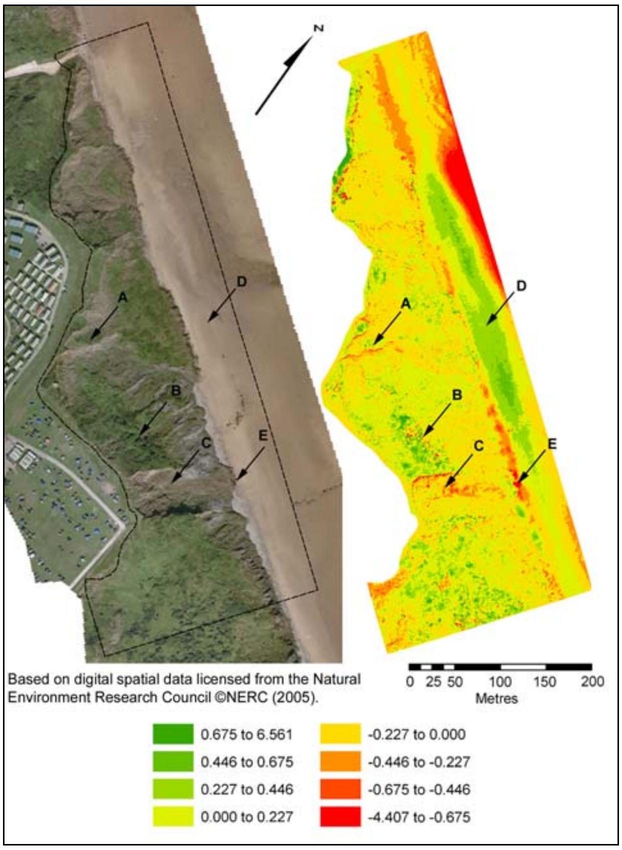

Figure 3. Elevation differences (metres) between integrated April 2005 and August 2005 DEMs. Corresponding August 2005 ortho-photo is included for reference.

5. DISCUSSION

The process of conducting monitoring surveys in the coastal zone has highlighted the benefits of a surface matching-based control approach. The TLS scans were controlled through conventional means, using GPS control points. However, adverse weather conditions, coupled with limited survey windows imposed by tides, meant that control measures were not as effective as they may have been under more favourable conditions. Consequently, some minor shifts and offsets existed between overlapping TLS point clouds. However, as demonstrated by Maas (2002), surface matching is a valuable tool for elimination of systematic error, and was successfully applied here in order to overcome these issues.

Robust surface matching proved effective in refining the overall registration solution of the TLS datasets, even in cases where no obvious systematic errors were evident. This approach offers significant advantages for data fusion, as minor mis-alignments can be eliminated. While differences may remain (e.g. as a result of the differing acquisition techniques), these are more likely to appear as inconsistencies, evident through inspection of the post-match surface residuals. Importantly, robust estimation offers a mechanism for mitigating the influence of outliers and regions of difference between the datasets. This is essential for change detection or deformation analysis, ensuring that erroneous change artefacts are minimised.

ALS and TLS were found to be highly complementary for this application. The high spatial resolution of TLS demonstrates potential for fine-scale assessment of geohazard activity, which may be of value in detecting pre-cursor failure processes. However, clearly it is not feasible to survey extended stretches of coastline using TLS. Rather, the results presented here highlight the value of TLS for concentrated analysis of localised pockets of geohazard activity. Integration with ALS delivered improved spatial coverage and over wider extents provided a coarse indication of change. In this manner, the integration of ALS and TLS shows potential for multi-scale analysis of coastal geohazards, providing a practicable means for monitoring extended stretches of coastline. In addition, the capacity of the integrated airborne-terrestrial strategy for overcoming data occlusions is a major synergistic advantage. One weakness of ALS and TLS is the ‘blind’ nature of these techniques. However, most commercial ALS systems offer the capability to acquire corresponding imagery. Figure 3 indicates the value of contemporaneous imagery as a visual reference for interpretation of change. A more direct approach to the incorporation of this resource may be valuable for validation of the surface matching solution and verification of change.

In this research, ALS was found to provide an excellent source of control, offering a consistent and reliable surface model. This is in accordance with the findings of others who have successfully utilised ALS for control (e.g. Habib et al., 2004). By removing the requirement for control points, surface matching offers a registration technique which is automated and highly cost-effective. The increasing availability and diversity of terrain models at a range of scales, means that this is a technique which is likely to be of increasing relevance for multi-sensor dataset fusion. Although the strategy presented here is specific to coastal geohazard monitoring, robust surface matching is a flexible technique which is independent of the data acquisition technology, and well-suited to a range of scenarios. In particular, applications concerned with change analysis in dynamic natural environments are likely to benefit, especially where it proves expensive or hazardous to establish conventional control. Possible applications include glaciology, volcanology and landslide hazard analysis, as well as more generic data fusion applications.

6. CONCLUSIONS

Effective dataset registration is a major challenge in the dynamic coastal zone. In addition, the complex nature of the topography means that no one technique is generally optimal for assessment of coastal geohazard processes. Least squares based surface matching provides an effective solution for the integration of multi-sensor data, and overcomes the requirement for physical control points. However, discrepancies between the matching surfaces have the potential to degrade the registration solution. In response to this, this paper outlines the development of a robust surface matching algorithm, which incorporates an M-estimator function for down-weighting of regions of difference.

The application of this technique for the integration of airborne and terrestrial laser scanning datasets has been presented. This has highlighted the effectiveness of robust surface matching in improving the registration solution of TLS datasets, and has demonstrated the further advantages of surface matching for multi-temporal change detection. In addition, it is shown that the integration of airborne and terrestrial laser scanning point clouds produces significant synergistic benefits, particularly in relation to overcoming dataset occlusions, and facilitating multi-scale analysis. The potential of robust surface matching is evident for a range of environmental applications, particularly those likely to benefit from dataset integration, where there is an associated requirement for change detection.

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