Coastal Monitoring for Change Detection Using Multi-temporal LiDAR Data

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Abstract

Monitoring changes in landscapes is important for several environmental and geographical studies. This paper considers a coastline change detection approach using multi-temporal data captured by Light Detection And Ranging (LiDAR) technology. The proposed method consists of four steps. In the first step a heightmap is generated from LiDAR data. The second step represents the core of the proposed method. In this step dense optical flow of the multi-temporal heightmaps is computed, yielding motion vectors for each point. In the third step, points with similar motion vectors are clustered. In the last step a displacement for each cluster is estimated, representing the movement of soil. An evaluation of the approach shows a 91.897% accuracy when estimating displacements and a 93.710% accuracy when detecting displaced areas.

Keywords: change detection, optical flow, LiDAR

1 Introduction

Monitoring coastal changes is an important task for several studies. It is interesting from a geographical perspective to study the trends of local landscape changes. Such studies are also important for the economy. Various area utilisations can be efficiently planned by having priori knowledge about certain landscapes and their changing tendencies. Coastal areas represent a very dynamic case regarding landscapes. Constant tidal activity washes up and washes away soil from the surface. Such behaviour results in an ever-changing shape of coastline, especially in respect to salt pans. Frequent evaporation and flooding of such areas cause an accelerated process of the previously-mentioned surface changes. Such areas have many changes in the short term and are, therefore, excellent test sets for the change detection approaches of coastal data.

This paper presents an approach for the detection and estimation of coastal surface changes over a certain time-span. Surface data were obtained by LiDAR technology. The result of the presented approach are displacement estimations of certain parts of the coastline, where each point belonging to the displaced area is labelled. The paper is organised into 6 sections. Section 2 gives a short overview of related work. Section 3 provides a short summary on data acquisition and the test area. Section 4 describes the procedure for estimating surface change detection. Section 5 presents the results of testing. A summary of the paper is given in Section 6.

2 Related work

Many studies are engaged in coastal monitoring. Most of them focus on extracting the coastline and not computing the actual changes. Xu-kai, Xia, Qiong-qiong and Ali Baig [20] proposed an approach for automated coastline extraction using the Otsu algorithm and Canny edge detection [5]. Bouchama and Yan [4] proposed an approach for detecting changes between two datasets using a window-to-window comparison and SURF features for alignment. Bo, Dellepiane and De Laurentiis [3] extracted the coastline using an approach based on the local contextual information of remotely sensed data. Niedermeier, Romaneen and Lehner [16] detected the coastline using an approach based on wavelet methods. Alesheikh, Ghorbanali and Nouri [1] present an approach for coastal change detection based on a combination of histogram thresholding and band ratio techniques. A semi-automatic approach based on fuzzy connectivity concepts for the coastline extraction from SAR images was proposed by Dellepiane, De Laurentiis and Giordano [7]. Ali [2] proposed an approach that represents coastlines as curves that are divided into segments of the same length in a multi-temporal dataset. At each such corresponding segment, between the preliminary and postliminary acquired data, an Euclidean distance is computed that represents the amount of coastal displacement.

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3 Data acquisition

The data used in this paper were obtained by the laser remote sensing technology called airborne LiDAR. It is considered to be the most advanced remote sensing technology at the moment. Conceptionally it is similar to a RADAR or SONAR, with the main difference being the wavelength of the signal. LiDAR emits a series of laser pulses towards the surface where they reflect and travel back to the device. As the speed of light is constant, the distance can be determined by the time it takes the pulse to travel from and back to the device. Such a procedure is repeated under different scan angles so that it forms a line, as seen in Figure 1. Having a capture frequency of over 200.000 pulses per second and density of more than 40 points per square metre [18], a very detailed representation of the world can be obtained. LiDAR technology is also capable of penetrating through vegetation and recording the terrain beneath. The data are georeferenced using a GPS system for positioning and an inertial measurement unit (IMU) for angle determination of the emitted pulses [14, 12]. Data are stored as a three-dimensional point-cloud without a topology. Water areas, on the other hand, are troublesome, as low reflectance of light on water results in a low number of acquired points [19].

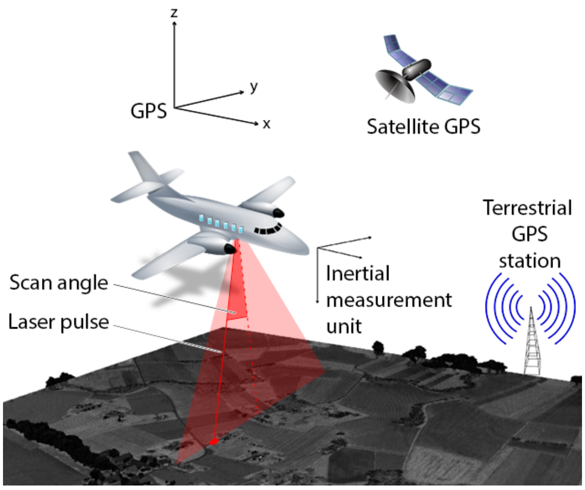


Figure 1: Data acquisition with LiDAR technology.

The data for testing the proposed approach were obtained at the Seovlje salt pans located near Portoro, Slovenia. Data were obtained in the years 2008 and 2010 and is already classified.

4 Surface change detection

Surface movement in geography is considered as a visible sliding of soil from its original position [21]. Changes on the coast can be considered as movement of the surface towards or away from the current coastline. An example is shown in Figure 2. In such a case, a rigid translation can be considered. The proposed approach is based on this assumption. A rigid translation is considered as a gradual changing of the coastline's shape. This assumption does not suffice for coasts that have suddenly changed the curvature of the coastline such as man-made embankments or excavations of an area. The approach consists of four main steps, as described in the next four subsections.

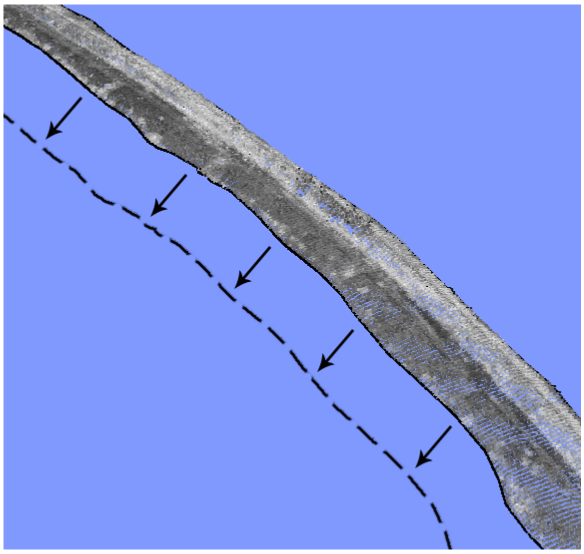


Figure 2: Displacement of the coastline.

4.1 Heightmap

In the first step a heightmap is generated from the input point-cloud. The resolution of the heightmap is dependent on the density of the obtained LiDAR data. The mapping requires an interpolation method, as points from the point-cloud do not coincide with the points on the heightmap. The inverse distance weighting (IDW) method [6] is used in the proposed approach. Using this interpolation method a height value is estimated using information from neighbouring points. The weight of each point within the neighbourhood is inversely-proportional to the power of the distance. A greater number of neighbours results in a smoother heightmap. The neighbourhood of the nearest 5 points is used for the proposed approach. The result of a heightmap is shown in Figure 3.

4.2 Optical flow

The calculation of optical flow is the key step of the proposed approach. It represents a motion estimation of objects within a scene and is defined as an apparent motion of intensity patterns on the scene [17]. Sparse and dense optical flows exist. A well known method for sparse optical flow was proposed by Lucas and Kanade [11]. It estimates motion vectors at feature points. Dense optical flow, on the other hand, provides a motion field consisting of motion vectors for each heightmap point. Such methods were

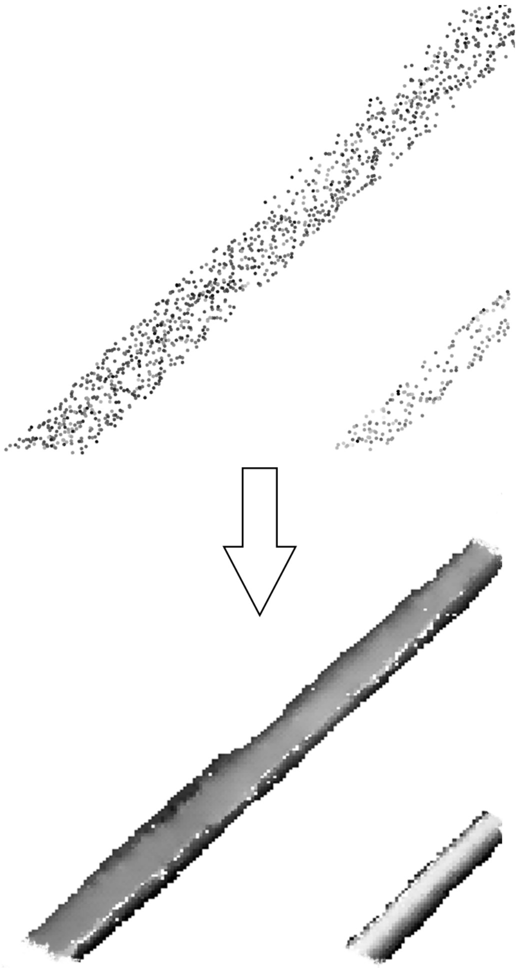


Figure 3: The representation of point cloud mapping to a height grid. The lower image represents a heightmap of the upper point cloud.

presented by Horn and Schmuck [9] and by Farneb [8]. The latter is used in the proposed approach as it yields more robust results.

The main idea of the optical flow computation procedure proposed by Farneb is to find a best fit between the point neighbourhoods of two heightmaps. Each neighbourhood is represented by a quadratic polynomial. Such a polynomial is obtained from polynomial expansion [8], based on normalised convolution, as proposed by Knutsson and Westin [10]. By assuming that the motion is gradual, a certain area of the corresponding point in the postliminary acquired heightmap is examined for the best fitting polynomial. In the case of the motion being sudden, meaning that is does not progress slowly over time, may lead to less accurate motion estimation. The distance between the polynomial on the first heightmap and the best fitted polynomial on the second represents the size of the motion vector. The angle of the vector is computed using the following equation:

$$\theta = \arctan\left(\frac{p_{2y} - p_{1y}}{p_{2x} - p_{1x}}\right). \quad (1)$$

Figure 4: A motion vector field.

A field of such vectors represent those motions that have occurred between two heightmaps over a certain time span, as shown in Figure 4. At this point the motion vectors are mapped from the heightmap to the point-cloud.

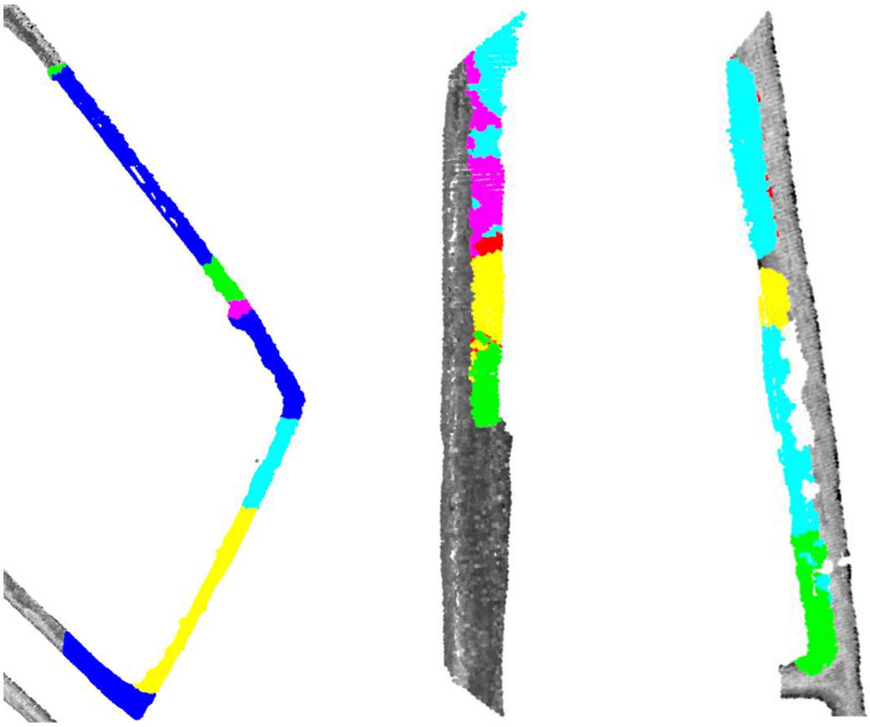
4.3 Point clustering

The result of the procedure described in 4.2 is a field of vectors, each representing motion at a point in the point-cloud. A clustering procedure is proposed for uniting points with similar motion vectors. The proposed clustering uses two criteria for determining whether a point is a part of the cluster or not. The first is the angle of the motion vector. Points with similar motion vector angles are clustered together. As noise within the data distorts motion vector estimation, an angle threshold of 15° is taken into account. The second criteria is the distance between points. A threshold is used for the maximum allowed distance between points. The next step is to find candidate points to cluster. A kd-tree nearest-neighbour search is used to find points within a certain radius [15]. Each newly inspected point that meets the criteria is added to the cluster and triggers a recursive method for finding new nearest-points. The procedure is finished when all the points have been inspected. In order to prevent false detections caused by noise, a threshold is introduced for a minimal number of points in a cluster. An example of clustering on test data is shown in Figure 5.

The goal of the proposed approach in this paper is to find changes of coastal surface. The computed clusters represent parts of land that had moved from their original positions.

4.4 Displacement of clusters

After clustering is finished, the positions must be determined as to where the clusters have moved on the postliminary acquired point-cloud. As each point has its own motion vector, an end position can be computed straightforwardly by adding the motion vector to the point coordinate. It is unnecessary for the calculated displaced points to represent the actual state of the second point-cloud. A kd-tree nearest-neighbour search is performed for determining the actual displaced points on the second-point cloud. Points within the same cluster have similar motion



(a) B190201 (b) B190204 (c) B204216

Figure 5: Dataset for testing with marked clusters.

vectors. Based on that fact, a global displacement vector for the cluster can be obtained as an average of all the contained vectors. The resulting vector represents the direction and amount of displacement the coastline has undergone.

5 Results

The proposed approach was implemented in C++ using the Qt 5 framework. Tests were performed as a single threaded process on a desktop workstation using the following hardware: Intel i5-3570K and 16GB of DDR3 RAM. The dataset used for testing were point clouds from binary LAS files. The average size of the test-set point-clouds was 100.000 points, and a grid with 0.5m resolution was used. The testing data represent those parts of the Seovlje salt pans that underwent the most change. Only those points recognised as ground were considered, because buildings and vegetation were not the studied subjects and would have unnecessarily slowed down the computation.

Two evaluation metrics were used for the proposed approach. The first evaluated the accuracy of the estimated displacements, while the second evaluated the accuracy of the correctly detected displaced areas. Reference data of surface movements had to be obtained for the purpose of evaluating displacement estimation. This was done by an expert in the field of geography. The tool used for measuring the reference data was LIDARLiVE [13]. As shown in Figure 6, this allowed a clear estimation of displacements by simultaneously displaying both point-clouds within a cross-section view.

The datasets and detected movements are shown in Figure 5. Test results for displacement estimation accuracy on 3 datasets are shown in Table 1. Verification of the obtained results show an average error of 8.103%. A slightly higher error value in dataset B204216 was the consequence of missing larger parts of data in some areas. The same datasets were used for evaluating the detection accuracy. The results are shown in Table 2. The proposed approach achieved an average of 93.710%.

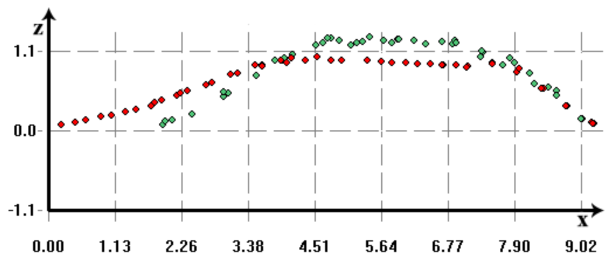


Figure 6: Cross-section view of two point clouds.

The results of the proposed approach were compared to the results of the coastline curvature approach introduced by Ali [2]. The same test-set was used for this purpose, however, the measuring of coastline displacements was limited to the areas of clusters that were detected by the proposed approach, due to consistency of result comparison. The values of the displacements and error are

Table 1: Results and comparison of the testing of displacement computation on 3 datasets with detected multiple displaced clusters.

Dataset	Cluster number	Actual displacement (m)	Proposed approach displacement (m)	Proposed approach error (%)	Coastline curvature displacement (m)	Coastline curvature error (%)
B190201						
	1	5.421	5.391	0.557	5.284	2.536
	2	4.966	5.220	5.125	4.662	6.108
	3	4.282	4.719	10.221	3.403	20.539
	4	5.142	5.550	7.938	5.292	2.922
	5	5.238	4.961	5.286	5.080	3.015
B190204						
	1	2.978	2.766	7.120	3.260	9.460
	2	2.390	2.548	6.605	1.916	19.820
	3	1.807	1.634	9.593	1.798	0.520
	4	1.390	1.584	13.964	1.400	0.720
	5	1.623	1.610	0.810	1.569	3.350
B204216						
	1	1.825	1.639	10.178	1.794	1.672
	2	2.035	2.120	4.185	2.148	5.538
	3	2.196	1.820	17.119	2.048	6.757
	4	1.821	1.552	14.749	1.704	6.405

shown in Table 1 under the coastline curvature approach columns. The average error of 6.383% shows that that the approach, proposed in this paper, is 1.720% less accurate than the coastline curvature approach. The reason for this is in the way of representing a shoreline. The proposed approach takes in account a wider area of the coastline, while the coastal curvature uses only the curve of the coastline which results in the coastal curvature approach being more sensitive to noise than the proposed approach.

The results of the proposed approach would be satisfactory for use within undemanding fields but would be inappropriate for tasks needing maximum precision. The main reason for the resulting error is the optical flow procedure, as it is difficult to find global parameter settings.

Table 2: Results of testing the accuracy of displaced areas.

Dataset	Coastline length (m)	Detected coastline length (m)	Error (%)
B190201	354.999	406.612	14.539
B190204	62.245	61,409	1.340
B204216	127.145	123.341	2.992

6 Conclusions

This paper proposed an approach for change detection of coastal surfaces using multi-temporal LiDAR data. The results show the displacement estimations of coastline areas. The part of the approach that is the main bottleneck is optical flow computation, as it is noise sensitive and highly dependent on the parameter settings. Future work should mainly be focused on optimising this part.

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