A NEW METHOD FOR ARTEFACT-FREE ESTIMATION OF SURFACE SLOPE FROM BATHYMETRIC LIDAR DATA

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ABSTRACT

When estimating the slope and aspect of a natural surface obtained by bathymetric Lidar scanning, discrepancies in the elevation data from neighbouring strips often cause artefacts. In this paper, a novel algorithm for slope estimation avoiding this kind of artefacts is presented. The algorithm is based on filtering the point data in the region of overlap using a set of scan angle based thresholds. Each threshold yields a data set with different selection of points from the neighbouring strips. Gradient estimates based on these data sets are then combined by either averaging or applying a trimmed mean type operation to obtain the artefact-free slope estimate. The algorithm is developed using bathymetric Lidar data and the obtained slope estimate of the seabed is used for the correction of the Lidar waveform data. The developed method is applicable in a wide range of situations where overlapping data from different sources need to be combined.

INTRODUCTION

Bathymetric Lidar scanning is gaining popularity in mapping the seabed in shallow waters. The method uses green lasers capable of penetrating relatively high water columns. The main application of bathymetric Lidar scanning is to obtain the digital elevation model (DEM) of the seabed. However, acquiring the entire return waveform of the laser beam enables additional information on the quality (i.e., sediment type, vegetation, etc.) of the sea bottom to be extracted.

In various applications of bathymetric Lidar data the slope of the seabed surface has to be estimated. For example, Yamamoto et. al. (1) used the slope as well as variables derived from it to assess the suitability of beach areas for sea turtle nesting in Florida. In the analysis of bathymetric full waveform Lidar data (2,3) the slope of the bottom surface is often used to correct the features derived from the waveform.

Estimating the surface slope can be a challenging task in areas where the strips of two neighbouring flight lines overlap. Deviations at either side of the overlap can cause significant errors in the slope estimate. An obvious solution to the problem would be to match the height deviances of the Lidar data by some kind of level matching and smoothing operation. However, this can be problematic in the presence of time-varying height drifts which leave significant artefact patterns in the slope data. Automatic calculation of a good quality slope estimate with minimal amount of smoothing and manual work is a challenge. Our method differs from strip quality control and adjustment methods like the ones presented in (4,5) by the fact that it is not meant to correct the point cloud but to generate error-free gradients in the presence of possible errors that are left to processed Lidar data set.

In this paper, we first illustrate the problem in slope assessment using conventional gradient calculation methods. The proposed algorithm, based on combining scan-angle-filtered surfaces is presented next. Our purpose is to produce a reliable estimate of the slope of the sea bottom surface to be used for the correction of the return pulse waveform of bathymetric Lidar data. We do not aim at estimating the error of the elevation data or correcting for it; this would not be feasible, as there are no well-defined structures or known reference points at the seabed. The data used was acquired using the HawkEye II bathymetric Lidar. The wavelength of the Lidar is 532 nm and the average point density is one point per 2.4×2.4 m^2.

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PROBLEM DESCRIPTION

The problem is illustrated in Figure 1 where, in the upper row, the data points belonging to the overlapping strips are presented using different colours. In panel c) all the data points from both strips are preserved, while in panel b) the data points are filtered so that only the points corresponding to scan angles less than a certain threshold are preserved from either strip. This effectively reduces the width of the region where the strips overlap. In panel a) the filtering angle is adjusted so that practically no overlap is seen. In the second row of Figure 1, raster surfaces obtained by applying the `gridfit` surface fitting method in the MatLab environment to the Lidar elevation data points are presented. In rows 3 and 4, the corresponding *x*- and *y*-directional gradient surfaces are shown. The gradients are calculated from the elevation raster using the MatLab `gradient` routine.

The figures indicate that this kind of straightforward approach to gradient estimation results in severe artefacts at the borderlines of the region of strip overlap. This significantly reduces the reliability of the results of further processing steps based on slope and aspect data.

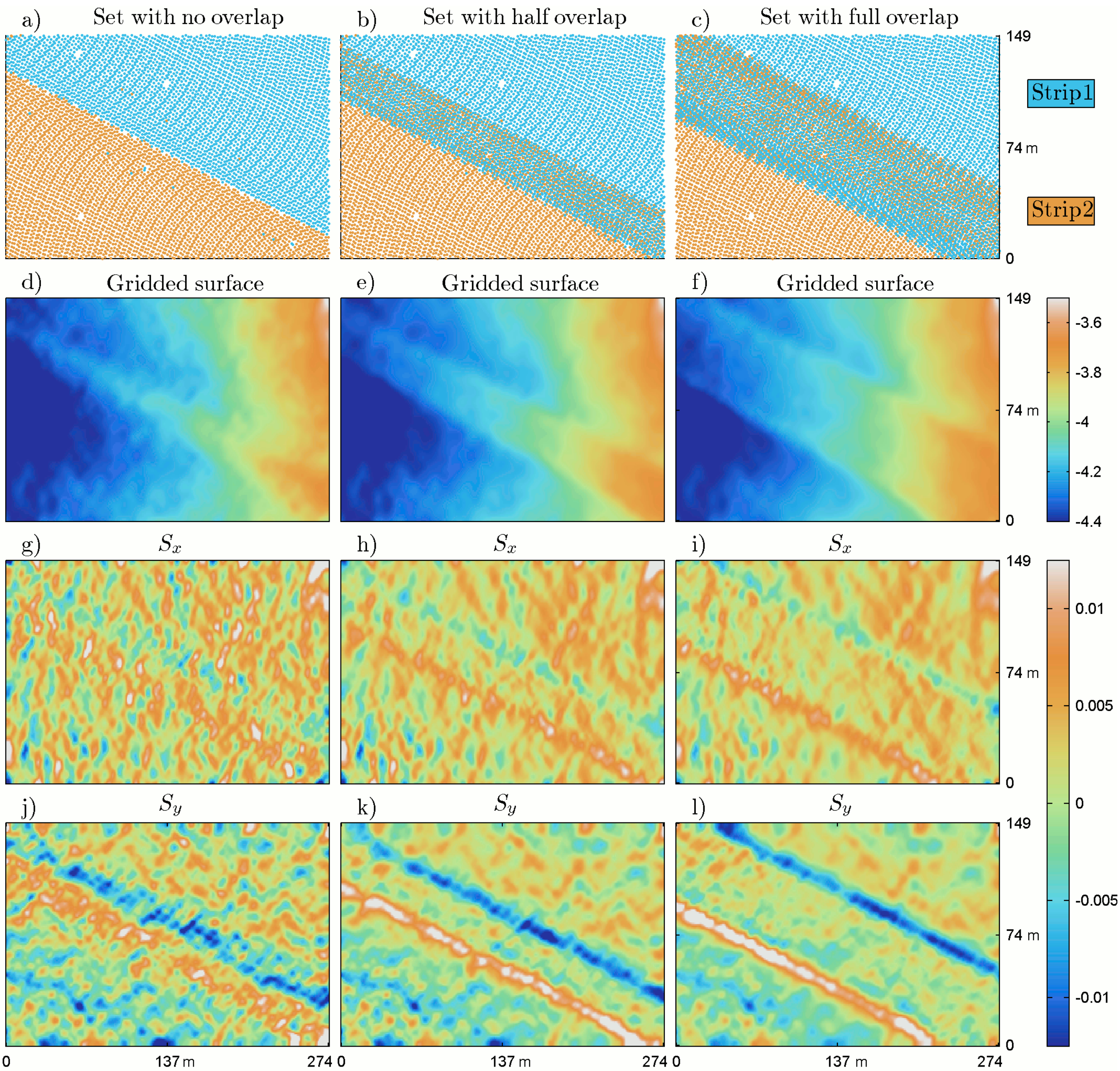

Figure 1: Artefacts in gradient rasters S_x and S_y due to disagreement in the elevation values at strip overlap. Note that the location of the error changes with the width of the overlap region.

METHODS

Let us denote the set of Lidar data points by $R = \{x, y, z, \alpha\}$, where x and y specify the location of the points, z denotes elevation and α denotes the corresponding Lidar scan angle (the Scan Angle Rank field in the LAS specifications) provided in the data set. Subsets R_{β_j} are extracted from the set R as follows:

$$R_{\beta_j} = \{\langle x, y, z, \alpha \rangle : \langle x, y, z, \alpha \rangle \in R \wedge |\alpha| \le \beta_j\}$$

where $j = 1...N$ is used to identify the filtered data sets according to the threshold values β_j of the scan angle. Consequently, R_{β_j} contains only those data points from R for which $|\alpha| \le \beta_j$. In our experiment, $N = 18$, i.e., 18 different filtering levels were used, yielding 18 sets of data points. See Figure 1 panels a), b), and c) for a selection example where $N = 3$. The number of sets is limited by the overlap of the strips and the resolution of the angle parameter in the flight data. The lower limit for the scan angle threshold is the value for which the point data from neighbouring strips does not overlap any more. In some occasions the filtering operation may produce gaps in the data set and a put back operation, described later in this section, is required.

Gridded surfaces D_j of the filtered data sets are estimated using the `gridfit` algorithm (6) to obtain corresponding raster data sets:

$$R_{\beta_j} \xrightarrow{\text{gridfit}} D_j(x, y),\ j = 1...N$$

We used the following parameters of the `gridfit` algorithm: overlap: 0.5; cell block size: 75; raster resolution: 1 m; smoothing parameter: 20. Resolution and smoothing parameters control the output resolution and acuteness of the resulting gradient raster, respectively.

The x- and y-directional gradients are calculated next for each gridded surface D_j using the `gradient` algorithm:

$$S_{x,j}(x, y) = \nabla_x D_j(x, y);\ S_{y,j}(x, y) = \nabla_y D_j(x, y),\ \ j = 1...N\ .$$

Two different schemes for combining the gradient raster data sets were tested. The first scheme (Method 1) simply involves calculating the average of the data sets:

$$\hat{S}_x(x, y) = \frac{1}{N}\sum_{j=1}^{N} S_{x,j}(x, y);\ \hat{S}_y(x, y) = \frac{1}{N}\sum_{j=1}^{N} S_{y,j}(x, y)$$

The alternative scheme (Method 2) involves sorting the magnitude values of the data sets and calculating the average of the k smallest magnitudes:

$$\breve{S}_x(x, y) = \frac{1}{k}\sum_{j=1}^{k} S_{x,(j)}(x, y);\ \breve{S}_y(x, y) = \frac{1}{k}\sum_{j=1}^{k} S_{y,(j)}(x, y)$$

where $S_{x,(j)}$ and $S_{y,(j)}$ are the j-th smallest magnitudes of the N x- and y-directional gradient raster data sets, respectively. This can be considered as a modification of the trimmed mean operation, where the trimming is performed according to the absolute value. The value $k = 10$ was used in our study to exclude eight values of highest magnitude from the averaging operation.

Put back operation for filling the gaps in the data

As the Lidar data points are scan-angle-filtered, gaps may be introduced into the data sets. This mainly happens at the edges of the survey area or when the Lidar survey lines' overlap is not the same for all survey lines. These gaps must be filled, because otherwise the interpolation/ smoothing operation could produce artefacts such as overshoots or flat areas.

The first step is to differentiate the strips from one another by numbering and to calculate the centre lines of the strips. If not available in the data, the survey line (or strip) number can be extracted from the GPS time and the centre line of a strip can be estimated by fitting a straight line to the (x,y) values of the Lidar point data from the particular strip.

The following steps are performed next. The points previously removed by scan angle filtering are considered one by one and if no point from the preserved set is found closer than the distance r, a gap is detected in the filtered data set and the particular removed point is considered to be a candidate to patch up the gap. The threshold r is determined experimentally from the average neighbour distance within one survey line. Subsequently, the candidate points are studied one by one and if any other candidates are found within the radius r that are located closer to their corresponding strip centre line, the particular candidate is removed from the set of candidates. All the remaining candidates are used to patch up the gap.

RESULTS

The results of the gradient estimation algorithm are presented in Figure 2. By comparing the panels of the figure it can be noticed that the proposed analysis essentially removes the artefacts due to strip overlap. Method 1 effectively smears the gradient artefacts over larger areas, while Method 2 seems to be more efficient in removing the artefacts altogether. Detailed examination of the results of Method 2 reveals, however, that this method introduces small amplitude noise to the gradient raster.

For quantitative evaluation of the proposed algorithm the elevation values of the strips 1 and 2 in the data shown in Figure 1 were replaced by values 0 and 1, respectively. This models the case where the actual surface is flat on both strips (i.e., the gradient is 0) and the height difference in the overlap region is entirely due to data disagreement between the strips. The evaluation is performed by calculating the residual sum of squares (see Table 1) for three processing schemes: simple gradient calculation without scan angle filtering, Method 1, and Method 2. The results indicate that scan angle filtering significantly reduces the artefacts in slope calculation and that Method 2 should be preferred for combining the scan-angle-filtered rasters.

Table 1. Results of quantitative analysis of the performance of the proposed algorithm.

	True gradient	Gradient calculated without scan angle filtering	Gradient of Method 1	Gradient of Method 2
$\sum_x \sum_y (S_x(x,y)-0)^2$	0	2.831	0.760	0.098
$\sum_x \sum_y (S_y(x,y)-0)^2$	0	15.716	3.786	0.277

DISCUSSION AND CONCLUSIONS

The proposed method for estimating surface gradients in the regions of strip overlap was shown to yield a smooth and artefact-free estimate of the slope. In our implementation, all scan-angle-filtered rasters were saved separately to a hard disk for further combining. As a result, the memory requirements and calculation time increase considerably with the spatial resolution, the resolution of the scan angle parameter (i.e., the number of individual angle filtered data sets) and the amount of data. In our case the method was used for gradient estimation of a bathymetric Lidar data set of an area covering 8 km^2. Gradient calculation of the whole data set of over 1.5 million data points using Method 2 took 50 minutes on an 8-core workstation using MatLab implementation.

The problem of errors in Lidar data in the regions of strip overlap has been addressed by several studies. In (4), the author estimates the planar accuracy of the Lidar data by fitting surfaces to well-defined structures (roofs of houses, for example) in the data. By the displacement of the surfaces fitted to the data from two neighbouring strips the planar accuracy of the data is evaluated. In (5), a similar approach is taken: shift in the surfaces obtained from the data of two neighbouring strips is estimated in three dimensions in a sliding window. In this study, height as well as planar accuracy of the Lidar data are assessed and only smooth surface areas are considered in the analysis. The problem addressed in our study differs from those described in (4) and (5), as we are not interested in the elevation values, but aim at a reliable and artefact-free estimate of the surface gradient instead. In addition, our main focus is on relatively smooth surfaces such as seabed and natural terrain instead of built environment. We apply the presented method to the correction of pulse waveform data of bathymetric Lidar in a multistep algorithm for automatic classification of the sea bottom. However, the presented method can be adapted for various situations, where the point data of two or more data sets has local disagreements such as combining the data of two point clouds measured at different times and using different equipment.

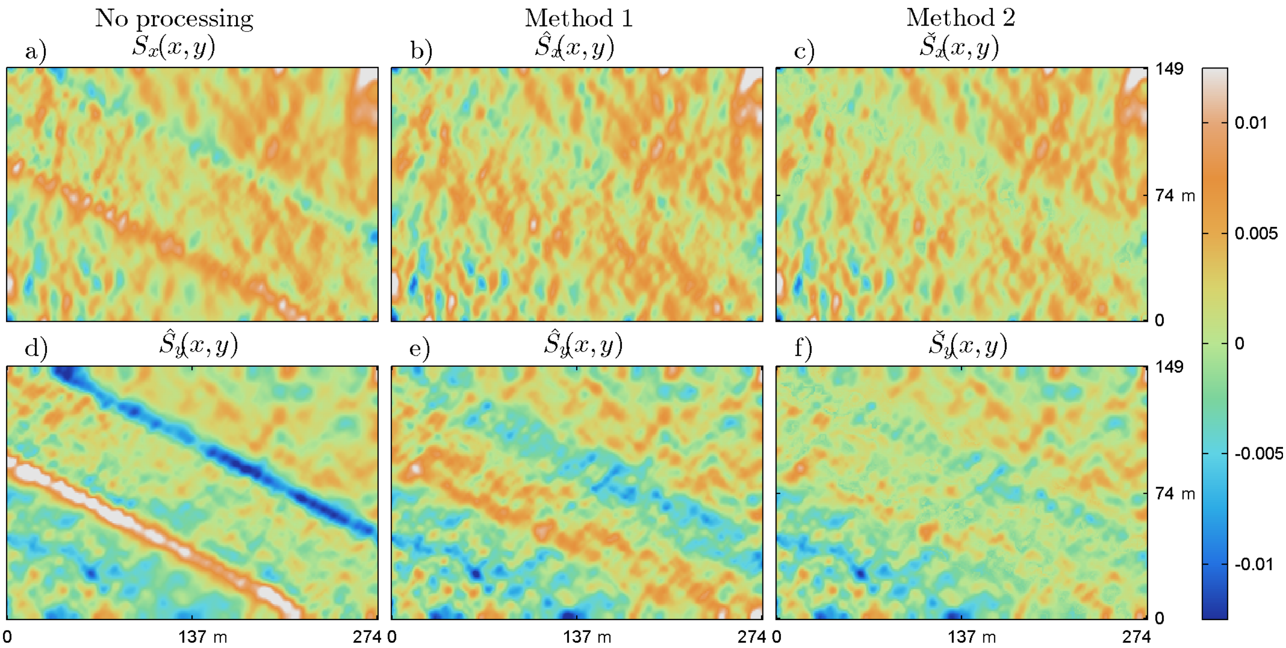

Figure 2: Comparison of results between the gradient estimation algorithms.

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