# Integration of intensity information and echo distribution in the filtering process of LIDAR data in vegetated areas

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## Abstract:

Accurate digital terrain models (DTM) are crucial for many applications in coastal management, such as simulation of flood risk scenarios. Airborne LIDAR sensors generate dense height information of large areas for the derivation of suitable DTM in an efficient manner. However, the accuracy and reliability of the LIDAR DTM points suffer if the laser beam interacts with vegetation. Several filter algorithms were developed, which usually apply geometric criteria to eliminate the vegetation points. However, in areas of very dense vegetation and rough terrain, where only few laser pulses are able to penetrate the canopy, such processing often fails resulting in an upward height shift of the derived DTM. In this paper additional features are proposed, which correspond to the reflectance characteristics of the backscattering objects, to support the filtering proccess. The introduced new algorithm uses intensity information and the distribution of multiple echoes for adaptive weight update in an iterative surface fitting procedure. The benefit of the integration of these new features in the filtering method is shown for several areas covered by different types of coastal shrubberies.

*KEY WORDS: LIDAR, vegetation, intensity, multiple echoes, filtering*

## 1. Introduction

### 1.1 Motivation

In the last few years airborne LIDAR arises to one of the most important techniques for the derivation of area-wide digital terrain models. The advantages of this contact free measurement method are especially noticeable in the coastal region of the German North Sea, where access for terrestrial surveying is limited due to dense vegetation on the islands and frequently flooded terrain in the Wadden Sea. The LIDAR DTM quality depends basically on the sensor and flight parameters (e.g., scanner device and flying altitude), the applied post-processing methods (e.g., strip adjustment and georeferencing), and the scene topography. In case of moderate surface roughness in non-vegetated areas LIDAR DTM usually provide a standard deviation in height of less than 15cm. However, if the laser beam interacts with vegetation, the accuracy and reliability of the LIDAR DTM points suffer depending on the type of plants and season. Especially, the plant height and density influence the penetration rate of the laser pulses. Low vegetation often can not be separated from the ground beneath, resulting in reflection composed of mixed signals, whose center of gravity is located above the terrain surface. Consequently, the measured time of flight and the resulting distance to the sensor are too short, leading to a bias (**height shift**). Tall vegetation may cause multiple echoes at various height levels, which can be resolved if the provided range resolution of the scanner system is high enough. Many filtering techniques developed for DTM generation rely on the assumption that the last echo represents the ground. However, even these echoes are frequently caused entirely by backscatter from low vegetation layers resulting again in a shorter distance measurement. Several filter algorithms were developed, which use geometric criteria to eliminate the vegetation points from the data set (see section 1.2 for more details). The most important requirement of these filters is the existence of a suitable number of ground points. However, the study area located at the coast of the German part of the North Sea is covered by various dense vegetation types, which prevent the penetration of the laser pulses in large areas. Another problem arises from the aspect that the vegetation often occurs in small valleys. Therefore, vegetation points are sometimes lower than the surrounding ground on the ridges. These facts lead to unsatisfactory results of common filter algorithms. In this paper a new method is introduced, which integrates the reflectance characteristics of the backscattering objects, in order to support the filtering process.

### 1.2 State of Research

Various filter algorithms for eliminating non-ground points in LIDAR data sets were developed considering different landscape types. Sithole (2005) provides a comprehensive overview about the existing methods, their classification depending on diverse criteria, a description of the ISPRS filter test (see also Sithole and Vosselman (2004)), and an approach of a new filter technique. Sithole distinguished the filter algorithms regarding data structure, neighbourhood, measure of discontinuity, single step vs. iterative, basic filter concepts, and external information. Four main groups were defined according to the following basic filter concepts:

- Slope based (e.g., Vosselmann, 2000)
- Block minimum (e.g., Wack and Wimmer, 2002)
- Surface based (e.g., Kraus and Pfeifer, 1998)
- Clustering/Segmentation (e.g., Brovelli, 2002)

The use of multiple echoes and reflectance information was another criterion. However, among all contributors of the ISPRS test only the algorithm of Brovelli (2002) considered the difference between the first and last echoes in the labelling process. The stored intensity values given for every LIDAR point were not yet integrated in any of the analysed filtering methods. However, several approaches for classification of objects from the LIDAR point clouds exploited this feature. For example, Moffiet et al. (2005) investigated the capabilities of the different returns (ground and vegetation, first, last, and single pulse) as well as the related intensity to classify diverse tree types. Tóvári and Vögtle (2004) used the intensity values among other features, in order to discriminate buildings, vegetation, and terrain.
A sound physical model of the complex interaction between the laser beam and distributed scatterers located inside the beam cone is a prerequisite for interpretation and analysis of full-waveform LIDAR data provided by some advanced sensor devices. Based on the radar equation Jelalian (1992) described the fundamental relations between the emitter, the reflecting object and the receiver applied to the lidar technique. Sensor and target dependent parameters are separated and an object dependent cross section is defined. Additionally, Wagner et al. (2006) pointed out the dependencies between the spatial variations of the cross section and the amplitude as well as the width of the reflected echoes. In the next step these theoretical considerations should result in practical applications of the intensity and echo width in classification and filtering algorithms.

The approach described in this paper is mainly based on robust filtering proposed by Kraus and Pfeifer (1998). This iterative algorithm uses linear prediction as interpolation method for the initial surface modelling. The residuals of the LIDAR points with respect to the surface of the previous iteration determine the weights for the next adjustment iteration using a special transfer function (Equation 1). Low weights are assigned to points lying above the fitted surface (probably vegetation), while points located beneath the surface (probably ground) are given a high weight. The algorithm stops, if the changes of the unknowns are below a predefined threshold or the maximum number of iterations is reached. Finally, a threshold with regard to the residuals is defined, in order to classify the LIDAR points.

$$p(r_i) = \begin{cases} 1 & \textit{for} \quad g < r_i \\ \dfrac{1}{1+(a\cdot(g-r_i)^b)} & \textit{for} \quad g \geq r_i \end{cases} \tag{1}$$

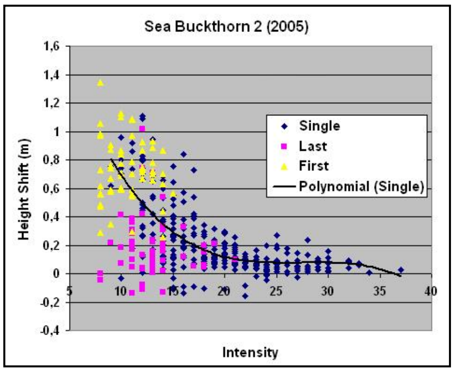
where $p(r_i)$ = weight of point i; $r_i$ = residual of point i; a,b = definition of steepness; g = shift in the direction of $r_i$

## 2. The new Filtering Algorithm

### 2.1 Initial Considerations

This part of our research project was focused on the analysis of the influence of different coastal vegetation types on the accuracy and reliability of airborne LIDAR data. Initially, the height shift caused by the vegetation was investigated based on several control areas. Additionally, the relationship between different object as well as data driven features (vegetation height and density or standard deviation in height) and the accuracy of the LIDAR data in vegetated areas was analysed (Göpfert and Heipke, 2006). Subsequently, the most meaningful features (e.g., intensity values) were used, in order to perform a supervised classification of the LIDAR data into predefined accuracy intervals. However, the features have the drawback that the accuracy intervals do not correspond to distinct and easily separable clusters in feature space, which is required for classification methods that partition the feature space into crisp regions assigned to the different classes. Considering a single vegetation type the height shift exhibits a rather continuous characteristic. Thus, in a new approach (Goepfert and Soergel, 2007) this issue was tackled by modelling the height shift with respect to the features using continuous functions. This function fitting process is realised in areas, where control measurements are available. Subsequently, the adjusted functions of the different features were used to estimate the height shift for LIDAR points within other regions of similar vegetation. Figure 1 visualises two examples of the modelled dependencies between the intensity values and the height shift for training areas of different size in the leaf-off period.

(a)




(b)

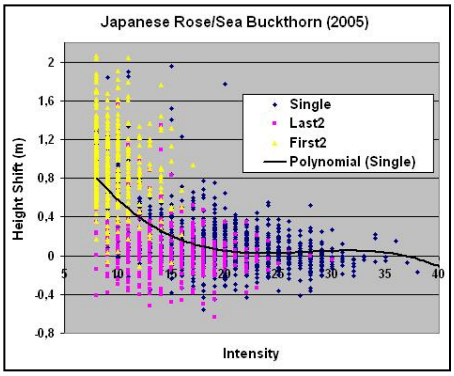



Figure 1: Dependency between intensity values and height shifts for multiple and single echoes of two areas with different size in leaf-off period: a) 297 single echoes, b) 1183 single echoes (Riegl-Scanner LMS-Q560)

However, the second method still has several drawbacks. On the one side multiple extensive control measurements are required as training areas in order to fit robust functions and guarantee the transferability to other regions. On the other side the larger (and thus more inhomogeneous) the training areas, the larger are the residuals of function fitting (see Figure 1). Due to the rise in the inhomogeneity of the vegetation height and density distribution, the significance of the intensity values suffers. Figure 2 illustrates this relationship: if the vegetation heights differ significantly in the area of interest, similar cross sections (and thus intensity values) can result for echoes in various heights above the ground. Therefore, the applicability of the intensity values depends on the size of the considered neighbourhood. Thus, the training areas of the second approach have to be small enough with respect to the homogeneity of the vegetation and large enough regarding robust function fitting. Furthermore, the fact that higher vegetation often occurs in valleys and therefore similar cross sections, which are related to different height shifts, are located in the same absolute height makes the situation even more complicated in larger training areas of considerable ground and vegetation variations (Figure 2).

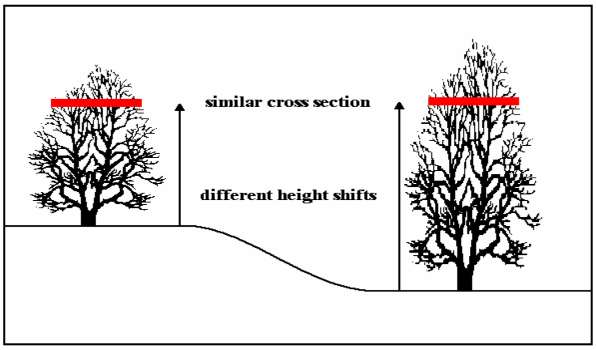



Figure 2: The correlation between the intensity values (corresponding to the reflecting cross section) and height shifts strongly depends on the homogeneity of the vegetation height and density distribution in the area of interest.

Additionally, other **statements** about the intensity distribution can be made by analysing Figure 1, which are important in designing a new filtering algorithm:

1. The higher the single echo is located in the vegetation, the smaller is its intensity value.
2. Single echoes exist with intensity values as well as height shifts similar to first reflections.
3. Due to a loss of energy caused by preceding reflections, which are above the detection threshold, the mean intensity of true last echoes is smaller than the same value of single undisturbed ground echoes.
4. The intensity of last echoes varies strongly depending on the object cross sections and the amount of pulse energy of the previous echoes. Because these influencing variables are difficult to separate, the intensity values of last echoes are less useful.

Besides the results of the data analysis theoretical considerations support the use of intensity in the filtering process. The intensity values given with the data might be derived from the measurements in different manners by the providers. However, in any case they represent a function of the signal amplitude, which depends on the spatial variation of the cross section (see Wagner et al., 2006). Reflectivity, directionality of the scattering, and the effective area of the reflecting surface of an object are combined in the concept of the cross section. This cross section is defined to model properties of individual point targets. In order to address distributed targets, a so-called differential cross section is more appropriate. Therefore, the amplitude of the echoes as well as the intensity values of the LIDAR points are related to the characteristics of parts of a complex object, such as plant structure, and consequently to the vegetation density. In the basic case of normal incidence with uniform intensity, flat bare ground yields a homogeneous cross section (coinciding with the circular footprint) as well as a narrow pulse width and high amplitude, whereas for a signal consisting of terrain and low vegetation contributions the pulse width is expanded and the amplitude is attenuated. Considering coastal shrubberies in the leaf-off period, the higher the echo in the vegetation, the thinner are the branches, which contribute to the cross section. Therefore, the amplitude as well as the intensity values also decrease theoretically for elevated LIDAR points.

### 2.2 The New Approach

While in the previous methods the intensity directly participates in the calculation of the height shift as one of the features, in the new algorithm it is used for the determination of the weights during an iterative robust surface fitting*. Several considerations support this indirect integration of the intensity in the process. For instance, if the estimation of the height shift is dominated by the feature intensity in the second approach, the resulting surface can strongly diverge from the related LIDAR heights. In order to avoid this effect, the LIDAR heights are the only direct feature (observations) in the new algorithm, while the intensity values take part in the determination of the weights. Another reason is related to the theory of the adjustment process. Originally, the weights are calculated using the a priori standard deviation of the associated observations, i.e., the heights of the LIDAR points. The broader the echo width and the lower the separability of the amplitude as well as the intensity from noise, the more uncertain is the determination of the exact position of the echo. Therefore, a lower intensity value indicates a larger standard deviation and subsequently a smaller weight.
The new algorithm performs an iterative surface fitting in a local neighbourhood centred in the currently considered single or last echo. The method starts with an initial estimate of a local first or second order surface (observation equations in Equation 2) using equally weighted single and last echoes of one flight strip in a moving window (yellow circle in Figure 4a).

$$r_i = f(\hat{a}, x_i, y_i) - z_i \qquad (2)$$

where $r_i$ = residual of point i; $x_i, y_i$ = coordinates of point i; $\hat{a}$ = vector of the unknowns (parameters of the surface); $z_i$ = observation of point i

The resulting residuals are analysed in order to update the weights of the observations iteratively. The weights consist of two parts. Equation 1 directly transfers the residuals into the first component of the weight $p(r_i)$, assuming that points below the surface belong to ground and points above the surface to vegetation. The second part $p(I_i)$ is calculated by analysing the intensity for single echoes and the echo distribution for last echoes. For this purpose two linear transfer functions are determined:

1. If at least three first echoes are available in the neighbourhood, a weight of 0.2 is assigned to their mean intensity defining one point of the **intensity transfer function** (referring to statement 2 in section 2.1). Otherwise, a weight of 0.4 is given to the mean intensity of those single echoes with the largest negative residuals (probably vegetation – statement 1). These empirical values take into account that with a higher probability the first echoes belong to vegetation. The other point of the transfer function is determined by the mean intensity of the single echoes with the largest positive residuals (probably ground – statement 1). These points receive a weight of 1. Following statement 3 only the intensity values of the single echoes are considered in this part of the algorithm. The linear intensity transfer function (Figure 3), which is bound to weights between 0 and 1, is updated iteratively depending on the residuals.
2. As pointed out in statement 4 of section 2.1 the intensity of last echoes is less useful. Therefore, their second weight component in the adjustment process is defined by the height difference to their related first echoes. This concept is based on the assumption that the probability for a last echo to stem from terrain increases with this difference. The **echo distribution transfer function** is determined by the echoes with the largest difference (weight 1) in the considered window and a notional difference of 0m (weight 0.2).

* The basic concept of robust filtering can be found in Kraus and Pfeifer (1998).

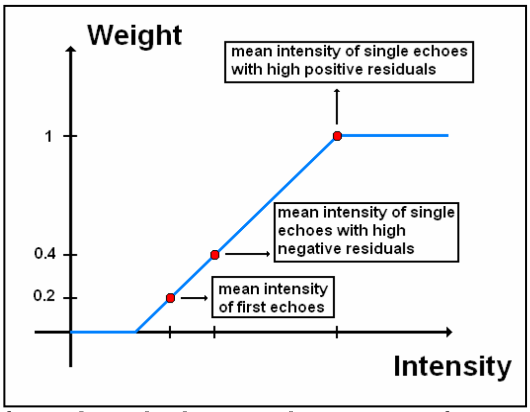



Figure 3: Determination of partial weights by using the intensity information in combination with the residuals of the previous surface fitting

$$p_i = p(r_i) \cdot p(I_i) \qquad (3)$$

where $p_i$ = total weight of point i
$p(r_i)$ = weight component of point i based on the residual
$p(I_i)$ = weight component of point i based on the intensity or echo distribution

In order to calculate the overall weights of the LIDAR echoes, the values defined directly by the residuals and the weights resulting from the analysis of the intensity and echo distribution are multiplied (Equation 3). The weights are updated according to the mentioned rules and the process stops after a predefined maximum number of iterations. Finally, the residual of the central LIDAR point is stored and the mask continues to the next last or single echo in the file. After processing all LIDAR points in the file the filtering is performed by comparing the residuals with a defined threshold.
Due to the dependence of the intensity values on features of the laser scanning devices, such as temporal pulse stability and the applied intensity measurement method, their applicability is checked for every iteration and window position according to the statement 1 in chapter 2.1. If the single echoes below the fitted surface have smaller intensity values than the points above, this constraint of the model is met and the intensity is used in the filtering process. Otherwise, only the first part of the weight, which is directly derived from the residuals, is used. The information “Intensity used” in the experiments (see below) refers to this test.

## 3. Results

The experiments are based on three flight missions and several training areas, which were surveyed by using tachymetry and GPS techniques. The data for the first mission were collected in March 2004 during a measurement campaign of the company TopScan with an ALTM 2050 scanner from Optech covering the East Frisian island Juist. The flying altitude was 1000m and the system provided an average point density of 2 points/m$^2$. Most of the investigations were carried out using data collected by the company Milan-Flug GmbH covering the region of the East Frisian Island “Langeoog” in leaf-off periods (April 2005 and 2006). During these campaigns a LMS-Q560 sensor (Riegl company) was used. From 600 m altitude the system provided an average point density of 2.9 points/m$^2$. The training areas consist of several populations of coastal shrubberies, such as Japanese rose, common sea buckthorn, and creeping willow. A detailed description of the reference data can be found in Göpfert and Heipke (2006).
The experiments in this section focus on the verification of the benefit, which is obtained by integrating intensity and multiple echo information in the filtering process. Two initial tests quantify the influence of the neighbourhood size (Table 1) and the number of iterations (Table 2) on the surface modelling accuracy with respect to the control measurements based on the

training area “Willow 2” in strip 1 of the flight mission “Langeoog 2005”. Additionally, they determine suitable values of these two parameters for the subsequent investigations. The parameters a and b of the function for robust filtering (Equation 1) are set to 1.5 and 2, while 0 is assigned to g for all the following tests.
In the first experiment the surface fitting is performed in 3 iterations (according to the findings in Table 2) using a plane concerning neighbourhoods of different area (Table 1). If the size of the moving window is enlarged, the mean value and the standard deviation of the differences between the true (control measurements) and the fitted surface increase. With larger windows the adjusted plane is not able to model the variations of the real surface with adequate accuracy. The radius is limited to 2.5m in the further analysis as a suitable compromise based on the following considerations. On one side the relatively large value is chosen, in order to preserve a minimum number of points for surface fitting as well as for the discrimination of vegetation and ground echoes based on the residuals. This successful distinction is required for robust filtering as well as for the determination of the intensity transfer function. With respect to this separability of the echoes a suitable radius depends on the penetration rate of the laser beam in the current vegetation. Enough points, which conform to statement 1 in section 2.1 (test for the use of intensity), should exist in the mask for the applicability of intensity in the algorithm. The higher percentage of the “used intensity” in larger neighbourhoods (last column of Table 1) supports these considerations. On the other side a larger radius decreases the accuracy of the fitted surface and the quality of the intensity transfer function in areas with inhomogeneous vegetation (see also Figure 1 and 2).

Table 1: Influence of the size of the defined neighbourhood on the mean and standard deviation of the differences between the true (control measurements) and the fitted surface, number of considered points, and the percentage of window positions with used intensity (control area “Willow 2” in strip1 of flight “Langeoog 2005”)

| **Radius (m)** | **Mean (cm)** | **Std. Dev. (cm)** | **Number of Points** | **Intensity used (%)** |
|---|---|---|---|---|
| **1,5** | **5,12** | **7,70** | **24** | **73,7** |
| **2,0** | **5,33** | **7,98** | **42** | **77,7** |
| **2,5** | **5,41** | **9,08** | **63** | **81,2** |
| **3,0** | **5,68** | **10,85** | **92** | **84,5** |
| **5,0** | **7,83** | **19,20** | **250** | **95,1** |

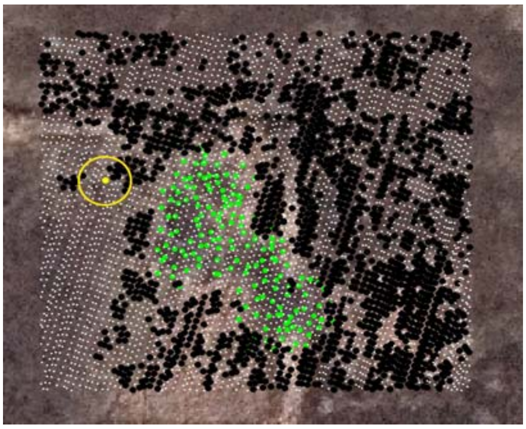
Table 2 illustrates the influence of the number of iterations on the accuracy of the method. Obviously, the mean and the standard deviation of the differences between the true and the estimated residuals decrease continuously and a stable solution is achieved after a few iterations, which is an indicator for the applicability of the method. In the further analysis three iterations are used.

Table 2: Influence of the number of iterations on the mean and standard deviation of the difference between the true (control measurements) and the estimated surface, (control area “Willow 2” in strip1 of flight “Langeoog 2005”)

| | **Iterations** | | | | |
|---|---|---|---|---|---|
| | **1** | **2** | **3** | **5** | **10** |
| **Mean (cm)** | 7,021 | 5,479 | 5,413 | 5,408 | 5,408 |
| **Std. Dev. (cm)** | 10,375 | 9,146 | 9,078 | 9,073 | 9,073 |

The percentage of the LIDAR points, in whose vicinity the intensity values correspond to the residuals (see statement 1 in section 2.1), is above 90 % for most of the training areas, located in populations of different coastal shrubberies (Table 3). A lower percentage is observed for most of the areas of smaller point density. This result confirms the initial experiments related to moving windows of different size (Table 1). A potential explanation of this phenomenon takes the location of the training areas into account. The two test regions "Willow 2" and "Rose 2" are situated at the border of strip 2 of the campaign 2005. Due to the larger inclination of the laser beam compared to the nadir view the penetration rate and the variations of the cross sections are smaller. Therefore, the significance of the intensity may decrease at the border of the flight strip. The increasing standard deviations for the two test sites support this assumption. The applicability of the reflectance information is also limited to coastal shrubberies (Figure 4). While the points with the used intensity are sparsely and randomly distributed in the meadow and heath, this information is almost always integrated during the surface fitting procedure of points in the test side "Sea Buckthorn 2" (green dots in Figure 4a) and the region of shrubbery on the left border of the image (see the biotope mapping in Figure 4b). Due to the low vegetation heights and different backscattering cross sections of meadow and heath the significance of the intensity feature is poor. However, this underlines the usefulness of intensity values as one feature among others for classification purposes.

(a)



(b)


Figure 4: If the distribution of intensity values and the related residuals correspond to the theory in the area of interest (yellow circle in (a) – diameter: 5m), intensity is used for filtering (small white points), otherwise not (black points). The green points in (a) belong to control measurements for an entire population of Sea Buckthorn. Background: (a) orthophoto, (b) biotope mapping.

Table 3 summarises the mean and the standard deviations of the differences between the true (control measurements) and the fitted surface for all test sites and flight campaigns using different methods. In comparison to the initial fitting, the robust filtering forces the surface to the lower LIDAR echoes with respect to the control measurements in every test region. The integration of the reflectance information always enhances this effect. Additionally, the standard deviation decreases for 67% of the test sites by using the intensity based weights.
The discrepancies of the mean differences between the various test sites seem to a large extent to depend on their location in the flight strip. Due to suboptimal post processing by third parties the strips are somewhat tilted. This results in systematic offsets depending on the location within the flight strip. However, because of the small size of the test sites (average: 20m x 20m) this issue does not significantly influence the comparison of the methods discussed here.
If the variation of the ground increases, the use of the second order surface slightly improves the results. However, the trend is similar to the application of the plane.

Table 3: Information of the different control areas: overall number of LIDAR points, percentage of window positions with used intensity, number of points in the neighbourhood (r=2.5m), mean and standard deviation of the difference between the true (control measurements) and the fitted surface for the initial fitting, robust filtering, and robust filtering with intensity information

| Test Side | Number of LIDAR Points | Intensity used (%) | Number of Points in Vicinity (r=2.5m) | Plane (cm) | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Initial | | Robust | | Robust + Int. | |
| | | | | Mean | Dev. | Mean | Dev. | Mean | Dev. |
| **Juist 2004 (Scanner: ALTM 2050; Altitude: 1000m)** | | | | | | | | | |
| Rose/Willow | 4046 | 89,7 | 48 | **53,9** | 58,2 | **50,8** | 56,6 | **43,7** | 52,4 |
| **Langeoog 2005 (LMS-Q560; 600m)** | | | | | | | | | |
| Rose/Sea Buckthorn (Strip1) | 3015 | 99,8 | 63 | **15,0** | 17,4 | **12,7** | 16,6 | **11,0** | 16,4 |
| Rose/Willow (Strip1) | 497 | 99,4 | 57 | **20,6** | 7,4 | **19,6** | 7,2 | **18,1** | 7,1 |
| Sea Buckthorn 1 (Strip1) | 820 | 99,1 | 67 | **15,0** | 12,5 | **14,3** | 12,3 | **12,7** | 11,9 |
| Sea Buckthorn 2 (Strip1) | 574 | 91,6 | 60 | **16,5** | 11,1 | **15,7** | 10,5 | **13,9** | 9,3 |
| Rose 1 (Strip1) | 736 | 96,5 | 57 | **7,8** | 8,3 | **7,3** | 8,2 | **6,4** | 8,2 |
| Rose 2 (Strip1) | 450 | 91,8 | 62 | **6,5** | 4,2 | **6,3** | 4,1 | **5,5** | 4,2 |
| Rose 2 (Strip2) | 265 | 89,8 | 37 | **-2,4** | 5,4 | **-2,5** | 5,4 | **-3,7** | 5,6 |
| Willow 1 (Strip1) | 419 | 93,1 | 68 | **12,6** | 6,0 | **12,3** | 6,0 | **10,8** | 5,9 |
| Willow 2 (Strip1) | 453 | 81,2 | 63 | **7,0** | 10,4 | **6,4** | 9,8 | **5,4** | 9,1 |
| Willow 2 (Strip2) | 260 | 77,3 | 37 | **4,8** | 12,2 | **4,1** | 11,9 | **3,2** | 12,6 |
| Beach Grass (Strip1) | 705 | 87,2 | 59 | **13,8** | 20,6 | **13,7** | 20,6 | **12,8** | 20,7 |
| **Langeoog 2006 (LMS-Q560; 600m)** | | | | | | | | | |
| Sea Buckthorn 1 (Strip11) | 522 | 94,8 | 42 | **2,1** | 11,1 | **0,9** | 11,0 | **-1,3** | 10,7 |
| Sea Buckthorn 2 (Strip11) | 302 | 74,2 | 31 | **-1,9** | 10,5 | **-2,9** | 9,7 | **-5,5** | 8,0 |
| Sea Buckthorn 2 (Strip12) | 199 | 80,9 | 21 | **-1,4** | 10,2 | **-2,3** | 9,5 | **-4,8** | 9,0 |

## 4. Conclusions

A new filtering algorithm was introduced, which transfers the intensity and echo distribution of LIDAR points into weights for a locally adaptive iterative surface fitting approach. The method was investigated using different test sites covered by coastal shrubberies during leaf-off periods. The results show that the integration of the reflectance information slightly forces the fitted surface to the lowest LIDAR echoes regarding the control measurements in every test region. Furthermore, the new algorithm decreases the standard deviation of the differences between the true and estimated residuals with respect to robust filtering in many test areas.

However, the points for the intensity transfer function are determined only empirically. In future research the separability of the intensity values of the lowest and the highest echoes with regard to the previous fitted surface should be analysed using statistical tests. The significance of this feature can be further used, in order to decide about the integration of the reflectance information and subsequently to define the transfer function.

In future work additional features provided by modern full waveform sensors, shall be exploited. For instance, the pulse width can be a quality criterion by itself. It describes the uncertainty of the target surface and the range measurement for the related echo and can therefore be easily integrated in the determination of the weights of the filtering process.

The promising findings in this paper encourage us to investigate the transferability of the method to other vegetation types. For instance, the assumption that the higher the LIDAR echoes in the vegetation the smaller the cross sections and the intensity values, could also be true for deciduous trees during the leaf-off period, because, among others, the cross section is also influenced by the diameter of the reflecting branches.

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