Classification of lidar data into water and land points in coastal areas

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ABSTRACT:

Over the last years lidar has become one of the major techniques to obtain spatial data in coastal areas. Due to the fact that lidar systems can provide several 3D points per square meter and high height accuracy, lidar data is suitable for several applications in the field of coastmonitoring and coastprotection. Generally, a digital terrain model (DTM) is used as basic spatial information for applications like morphologic change detection and hydrological modelling. In order to generate a DTM in coastal areas from lidar data, a classification process has to be performed to separate the lidar points into water and land points. Only land points, representing the coastsurface, are used to calculate the DTM.

In this paper, we present a new method to classify lidar data in water points and land points. The original points of each flight strip are classified scan line by scan line. Several parameters which are directly related to each point as well as the point distribution within one scan line are used for the classification method. A fuzzy logic concept is applied to determine a membership value for every point belonging to the class water. Then, a threshold method is employed to classify the points of every scan line. Afterwards, classification discrepancies are detected and corrected by comparing height differences between neighboured water and non-water points. In order to achieve a more realistic classification result small isolated point groups of a certain class are removed. To illustrate the ability of the algorithm two examples with different characteristics (lidar scanner system, point density, point distribution etc.) are presented. The results are promising and constitute a proof-of-concept for the suggested method.

1. INTRODUCTION

Lidar has become one of the major techniques to obtain high accurate spatial data in coastal areas. The method delivers, depending on the lidar system and flight parameters, several laser points per square meter with high height accuracy. Large areas can be registered fast (e.g. Brügelmann and Bollweg 2002) and digital terrain models (DTMs) can then be interpolated from the individual 3D points. Generally, a DTM is used as basic spatial information for applications like morphologic change detection and hydrologic modelling. In order to calculate a DTM, a filtering process has to be performed to separate lidar points into terrain points and off terrain points (Sithole and Vosselman, 2004).

Within coastal areas, several regions are covered by water. Typically the lidar beam does not penetrate water. Hence, lidar points measured in water regions describe the water surface but not the DTM lying underneath. In order to obtain a DTM of high accuracy, another process must be included to identify water points and exclude them from the DTM calculation.

Depending on the available data sources different approaches are possible. Two general cases can be distinguished. In the first case simultaneous acquisition of lidar and multispectral data is assumed. In this case, the images can be used to classify water with common classification methods. Lecki et al. (2005) pointed out that high-resolution multispectral imagery and appropriate automatic classification technique offer a viable tool for stream mapping. Within their analysis, especially water was classified accurately. Mundt et al. (2006) demonstrated that the accuracy of classification significantly increases by combining images and height data. However, multicspectral images are not always acquired during lidar data capture. Thus, in the second case, only the lidar data is assumed to be available. Typically, lidar data providers deliver the original 3D points and an intensity value, which corresponds with the strength of the backscattered beam echo. Up to now, only a few approaches to use the intensity of lidar data for classification were published. Katzenbeisser and Kurz (2004) emphasized the fact that classification methods used for remote sensing images need to be adapted to intensity data. They pointed out that the intensity has only a useful information value within open areas where only one echo was detected. Hence, other criteria's have to be considered in order to filter water points from lidar data.

In this paper, we first summarize important physical characteristics of lidar data and previous approaches, which were carried out to separate water points in lidar data. Then, a new method is presented to classify lidar data into water and land points. Starting from original irregularly distributed lidar points, several parameters are derived and rated using a fuzzy logic concept. Several steps are taken after classification in order to detect discrepancies and enhance the classification result.

To illustrate the ability of the algorithm, two examples with different characteristics (lidar scanner system, point density, point distribution etc) are presented. Finally, this paper concludes with a summary and an outlook on further development issues.

2. STATUS OF RESEARCH

2.1 Physical characteristics of lidar data within coastal areas

In order to develop a suitable algorithm which is capable of classifying the lidar data (raw 3D-lidar points and intensity values) the physical characteristics of common lidar systems as well as the reflection of water and land areas have to be

considered. Generally, lidar systems operate in the near infrared range. Wolfe and Zissis (1989) describe the absorption of infrared radiation depending on the illuminated surface material and the wavelength. They pointed out that the absorption for water is significantly higher than the absorption for soil. This leads to the fact that the intensity of water points is regularly lower than the intensity of land points.
Additionally, as a result of the Rayleigh Criteria, calm water surfaces behave like a mirror. Thus, specular reflexion occurs. Depending on the spatial orientation of the aircraft, the emitted laser pulse and the water surface with respect to each other, in general only a small part of the emitted radiation returns to the detector. Often, a distance measurement can not accomplished successfully because the received radiation energy is not distinguishable from background noise. This leads to the fact that the point density of lidar data within water areas is often significantly lower than within land areas.

2.2 Filtering off terrain points and filtering water points respectively

The filtering of off terrain points from lidar data is a common and necessary step in order to derive a DTM. Many different approaches (i.e. Sithole and Vosselman, 2005 or Tóvári and Pfeifer, 2005) were published and provide accurate results (Sithole and Vosselman, 2004). Neglecting differences of the approaches it can be stated that high points (or segments respectively) in the vicinity of lower points are generally labelled as off terrain points.
In order to calculate an accurate DTM in coastal areas a filtering of water points is performed. Analogous to off terrain points water points do not belong to the surface and have to be removed from the data set. Water points have a lower height than the surrounding land points. Theoretically, an inverse strategy of filtering off terrain points is able to classify likely water points. However, the overall correctness of a classification using such an inverse filtering strategy is not satisfying due to the fact that common filter techniques use only geometrical relationships of neighboured lidar points or segments respectively. Hence, local minima like tidal trenches are detected, but they may be dry and thus the detected points actually belong to the DTM. Furthermore, completely filled tidal trenches or swales can not be detected because the water level height is nearly equal to the surrounding flat coastal area.

2.3 Previous approaches to extract water areas from lidar data

Brockmann and Mandlburger (2001) developed a technique to extract the boundary between land and water of rivers, and applied it to data from the German river “Oder”. Based on lidar data, the planimetric location of the river centre line as well as bathymetric measurements of the riverbed, the boundary was obtained within a two-stage approach. First, the height level of the water area was derived by averaging the lidar points in the vicinity of the river centre line. Afterwards, the DTM of all lidar points (including also points of the water surface) was calculated. Then, the 0 m contour line of the difference model of the lidar DTM and the water height level was derived. This contour line is called the preliminary borderline. Within step two, the bathymetric points of the preliminary water area are combined with all lidar points outside the preliminary water area. Then, a DTM representing the riverbeds instead of waterlevel was calculated. Afterwards, the final borderline was obtained by intersecting the DTM including the riverbeds and the height level of water area.

Brzank and Lohmann (2004) (see also Brzank et al., 2005) proposed another algorithm which separates water regions from non water regions based on a DSM calculated from lidar data. The main idea was to detect reliable water regions and expand them with the use of height and intensity. For that purpose local height minima were extracted from the DSM, which represent the potential seed zones of the searched water areas. This was followed by region growing procedure using height and intensity data of the grid points.

2.4 Evaluation of previous approaches

In order to classify water points within lidar data, only height information is not sufficient. At least one additional data source is necessary. Brockmann and Mandlburger (2001) used the 2D position of the river as prior information. Hence they knew approximately where water occurs. Assuming that a water area has lower height than the surrounding land, the border can be detected. Next to the 2D position and the lidar data, also bathymetric measurements are prior information of this method. Thus, this algorithm needs additional information which is not always available in our application, taking into account that form and position of tidal creeks are changing fast.
Brzank and Lohmann (2004) tried to use the intensity as additional criteria to classify water. The algorithm provides accurate results if the intensity of water points differs significantly from land points. However, due to the fact that the intensity is generally very noisy and strongly influenced by the lidar scanner type and used wavelength, type and water ratio of the illuminated area, the classification accuracy can be unpredictable. Thus, at least one criterion has to be implemented in a new algorithm. Furthermore, this method does not work with the original lidar data but uses grid data. This is a crucial disadvantage because lidar data is obtained strip wise and generally, parts of several flight strips are combined in order to calculate a certain grid. Depending on the flight planning, a time shift occurs between neighboured flight strips. Taking into account that the water level in coastal area varies with time due to the tide, several water levels of the same water area may thus occur in a grid.

2.5 Requirements of the algorithm to classify water points from lidar data

Based on the physical characteristics of lidar data and the evaluation of the previous approaches, the following requirements for a successful algorithm are defined:

1. The algorithm uses the original lidar data.
2. No additional data sources such as images or vector GIS data are permissible.
3. The point density is used as additional criterion.
4. The classification is done for every flight strip.

3. CLASSIFICATION OF WATER POINTS USING 1D-LIDAR PROFILES

The new classification method is based on the analysis of 1D-lidar profiles of the original raw data in combination with fuzzy logic. Each lidar strip is classified separately followed by a check across the scan lines. At first the lidar points of a strip are grouped into single scan lines. Then a membership value of class water (see equation 1) is calculated for each point of every scan line. The membership value depends on the parameters height, slope, intensity, segment length, point distribution and missed points (see section 3.1), the membership function and weight for every used parameter. Afterwards, the classification is done using a hysteresis-threshold-method. Finally, in order to detect and remove discrepancies, several steps are applied. They use the classification results of neighbouring scan lines to overcome the limitation of 1D profile classification. All classification steps are described in more detail in the following.

$$\mu(x) = \sum_{i=1}^{m} \delta_i \mu_i(x) \Big/ \sum_{i=1}^{m} \delta_i \qquad (1)$$

δ_i:	weight parameter i
$\mu(x)$	entire membership of class water for point x
$\mu_i(x)$	membership value water point x depending on parameter i

3.1 Employed parameters and membership function

For classification several parameters are used. The parameters are:

Height: The higher a lidar point is situated the higher is the assumption that this point is not a water point. Thus with increasing height the membership value for class water decreases.

Slope: The more the slope within the profile direction increases the more the assumption holds that the following point is not a water point. Thus, with increasing slope the membership value for class water decreases.

Intensity: As pointed out earlier a low intensity value is an indication for a water point. Thus, with decreasing intensity the membership value for class water increases.

Missed points: If holes occur from one profile point to next within the scan line, discrete point(s) are not measured. The appearance of holes is an indication for a water region. The bigger a hole between two neighboured points the higher is the assumption for the occurrence of water. In order to deal with points which are close to the border line between land and water the number of missed points is checked in both direction for every profile point. Only the membership value related to the smaller number of missed points is used further.

Segment length: Based on the determination of the missed points the number of contiguous points within a profile can be derived. Thus, every profile point is a member of a certain segment with a certain segment length. With increasing segment length the indication increases that the segment points are land points.

Point density: For every point the number of previous and following profile points within a certain distance s can be determined. The higher number is divided by the distance s. Thus, with increasing point density the membership value for class water decreases.

It has to be pointed out, that the parameters missed points, segment length and point density are related to the fact that generally the number of points within the water area is smaller than within the land area. The usage of all parameters is possible, but existing correlation should be considered.

In order to calculate the membership value for a certain parameter a membership function and thresholds are needed. Basically, every function which increases strictly monotonic (or decreases strictly monotonic) can be used. In our algorithm, a straight line is applied. The two resulting thresholds limit the application range of the membership function. Outside the application range the membership value is set to 0 or 1 depending on the parameter. Figure 1 illustrates the calculation of the membership value of the parameter height for a scan line. After selecting the two thresholds the membership value can be calculated.

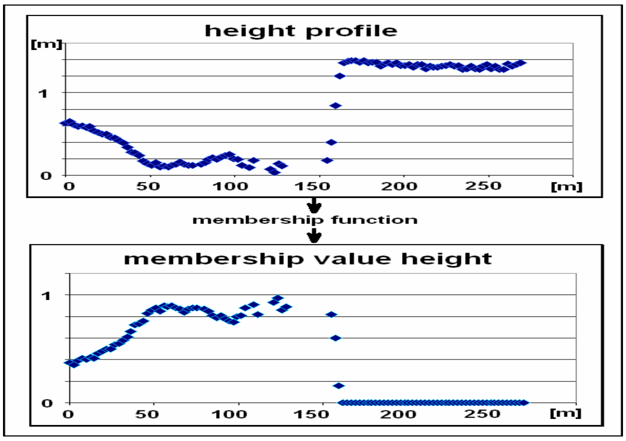

Figure 1: Deriving the membership value of the parameter height for a 1D-profile

After the calculation of the membership value for every scan line point using equation 1 the classification is done with a hysteresis-threshold-method. A low and a high threshold have to be defined. The classification of the actual point depends on the classification result of the previous point. If the previous point was classified as land the membership value of the actual point has to be higher than the high threshold to be classified as water. If the previous point was classified as water the membership value of the actual point has to be only higher than the low threshold to be classified as water.

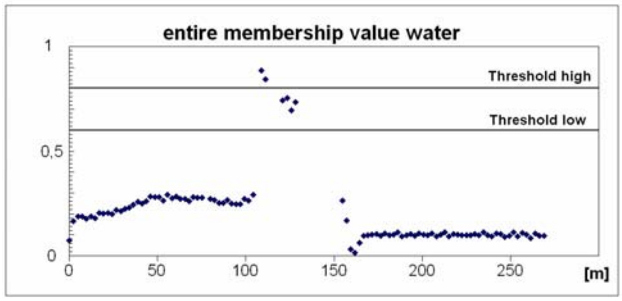

Figure 2: Classification of a 1D-profile with hysteresis-threshold-method

Figure 2 illustrates the classification process. The classification starts from the beginning (left side) of the profile. All of the first points have a membership value below the low threshold. They are classified as land points. Then, two points next to each other have a membership value above the high threshold, thus they are classified as water. The next four points of the profile are in between both thresholds. These four points are also classified as water points, because the previous point was classified as water and the membership value is higher than the low threshold. Thus, six points of the illustrated profile are classified as water points. It has to be mentioned that this classification depends on the direction, in which the profile is processed. If the classification starts from the other side (the end of the profile) the result may be not the same. In case of Figure 2 only the two points above the high threshold are considered to be water points if the classification starts from the right side.

3.2 Elimination of classification discrepancies and classification enhancement

Typically, classification techniques do not output error-free classification results. In order to obtain a suitable result classification discrepancies have to be removed. To detect and remove these discrepancies several steps are performed. They are all based on the fact that a water point next to a land point must have a lower height. At first, every individual profile is checked. If a water point next to a land point is found, the mean height of all water points within a certain distance is compared with the height of the land point. This mean height of several neighboured water points is used to suppress the influence of occurring waves. If the mean water height is equal or higher than the land height, a classification discrepancy occurs. Then, the average of the mean membership value of the water points and the membership value of the land point is calculated and compared to the average of the two thresholds used for the hysteresis-threshold-classification (see Figure 2). All points are labelled as water/land if the average membership value is higher/lower than the average of both thresholds.

Due to the fact that the algorithm is limited to 1D-profiles, the classification does not take neighboured points of the previous and next scan line into account. Therefore, in order to improve the result the second dimension is considered in the next step. Every scan line is compared to its left and right neighbour scan line. It is assumed that every correctly classified segment continues in the previous as well as the next scan line. A simple example may illustrate this assumption. Assuming a tidal trench which is filled with water is present in the lidar data. Several scan lines cross the water area. Assuming further that all scan lines are classified correctly, the classified water segment of the tidal trench for a certain line can be found next to this segment in the previous and the next scan line.

To check all classified segments of every scan line we use the following approach. First, every scan line is split into classified segments of the same class (see figure 3). Then, a rectangle with a width of three scan lines is generated, which is limited by the first and last point of the considered segment. Afterwards, all points from the previous and next scan line which are inside the rectangle are extracted. If no point of the extracted previous scan line and also no point of the next scan line have the same classification as the considered segment, the classification is defined to be wrong. Then, the classification of the considered segment is changed. Figure 3 shows an example of the check. The segment in the centre of the figure is detected as an isolated segment and the classification is changed while the segment in the lower right remains.

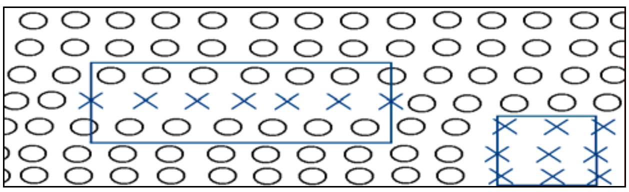

Figure 3: Check for isolated classified segments, crosses represent classified water points – circles represent classified land points, scan lines run from left to right

Subsequently, another classification check is performed. Again we use the assumption that if the height of a water point is equal or higher than a neighboured land point a classification discrepancy occurs. At first a certain number of neighboured scan lines is selected (e.g. 10). Then, a cross section is created for every point of each scan line perpendicular to the azimuth of the scan line. For every scan line the point with the smallest distance to the cross section is determined. The point becomes a member of the cross section if the distance is smaller than a predefined distance. Then, every cross section is checked analogous to the control of every individual scan line (see above).

After performing these checks the number of classification errors decreases. However, small classified segments may remain. Thus, the classification results may appear to be noisy. In order to enhance the classification further, small classified segments (of one scan line as well as perpendicular using several scan line) which are surrounded by classified segments of the other class are detected and removed. Finally, an almost consistent and smooth classification result can be obtained.

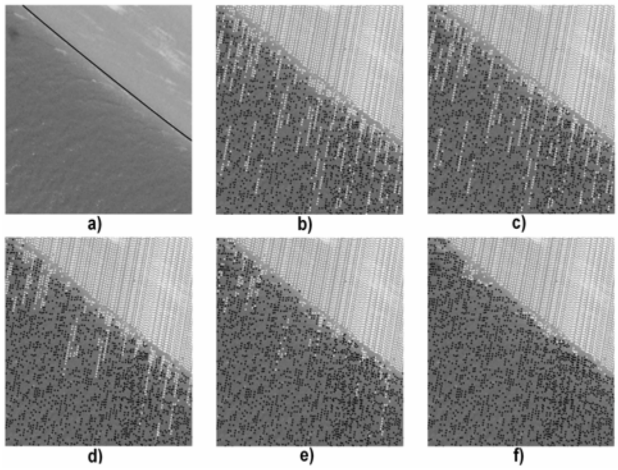

Figure 4: Elimination of classification discrepancies and enhancement, bright points represent land, dark points represent water. a) Orthophoto with digitized water-land-border, b) Classification result without further checks for discrepancies, c) Discrepancies within every scan line removed, d) Segments removed, which only occur in one scan line, e) discrepancies removed within perpendicular cross section, f) Small isolated segments removed

Figure 4 illustrates the process of removing discrepancies and enhancing the classification. Figure 4 a) shows a small part of the coast line of the East Frisian Island Langeoog. The added black line represents the border between water and beach. Figure 4 b) shows the classification result without checking for discrepancies. Bright points are classified as land. Dark points are classified as water. Within the water area some points are classified incorrectly due to the fact that they are part of long segments, which leads to a low water membership value. Furthermore, waves are present. Points on waves are higher, thus they have a low water membership value. The following images show the stepwise process of enhancement and removing discrepancies: 4 c) – discrepancies within every scan line removed, 4 d) segments removed, which only occur in one scan line, 4 e) – discrepancies removed within perpendicular cross section, 4 f) – small isolated segments removed. Finally, a smooth classification result without isolated points is obtained.

3.3 Automated Determination of used parameters in training areas

It is obvious that the selection of the used parameters, the membership function, the weights as well as the thresholds have a crucial impact on the classification result. Depending on the data (lidar scanner type, weather conditions etc.) only parameters which differ between land and water should be used. Because the user has to make these selections, he has to know the data rather well. In order to assist the user with his choice, at least one training area for water and for land is selected interactively. In our approach, the mean value of every parameter within the training area is determined. Based on these values, the user can better decide, which parameters are suitable for the classification.

3.4 Classic Fuzzy classification concepts vs. suggested approach

The classification algorithm uses fuzzy logic. Based on the fundamentals introduced by Zadeh (1965) also classification algorithms containing fuzzy concepts were developed and widely used (Traeger, 1993). Although these fuzzy classification concepts deliver suitable results we adapt the classic concept to overcome some difficulties.

In classic fuzzy classification concepts fuzzy sets (for example: low, medium, high) for every used parameter are defined. Based on membership functions exact values for certain parameters can be transformed into membership values for all defined fuzzy sets. Then, a rule base is defined which decribes how to combine all possible combinations of fuzzy sets of all used parameters. Finally, a defuzzification process is performed in order to allocate the result to a certain class. In our method we do not define fuzzy sets for the used parameters (for example: low height, medium height, high height) but transform sharp values of every used parameter in a membership value for the output class water by using two thresholds as well as the membership function. Thus, we do not have to define a rule base, which is a rather complex task. Assuming that we define three fuzzy sets for every used parameter (6) a total of $3^6 = 729$ rules have to be defined. Furthermore, the membership function of every fuzzy set has to be defined, too. According to the data, the membership functions have to be changed either in an automated process or by a human operator. Furthermore, practical tests with various lidar data pointed out, that the benefit of a parameter also depends on the used lidar scanner system. Thus, the rule base has to be designed taking the used lidar system into account. In our approach, it is easier to classify water areas, because the needed parameter values (thresholds and weights) can be derived by using training areas.

4. EXAMPLES

To show the capability of this approach two different examples are presented. The first example is taken from the lidar campaign “Langeoog 2005”. The East Frisian Island “Langeoog” was flown by the German company Milan using the LMS Q560 system of the company Riegl. The example contains a large see water area, mainly dry coast region and some water puddles. The second example contains a certain part of a flight strip of the campaign “Friedrichskoog 2005” which is situated at the coast of the North Sea next to the estuary of the river Elbe. The flight was carried out by the German company Toposys using their own lidar system Falcon II.

Within the first example 361.280 points were classified (see Figure 5). The classification was mainly based on the fact that the point density of the lidar points within water was significantly lower than over land. Additionally, the height also had a major impact on the classification result.

The second example (see figure 6) contains 998.029 lidar points. Due to the fact that the point density did not differ significantly between water and land, the classification was based on the parameters height, slope and intensity.

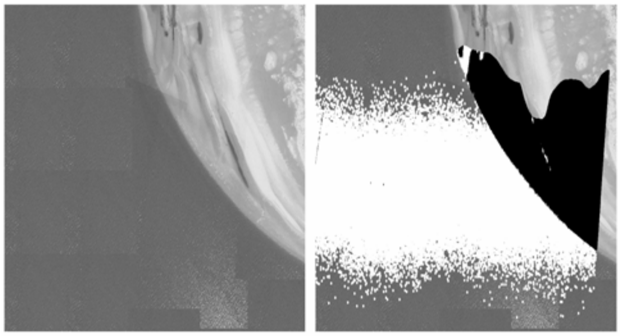

Figure 5: Classification of a part of a flight strip of the campaign “Langeoog 2005” – left: lidar DTM, right: classified water points = white dots, classified land points = black dots

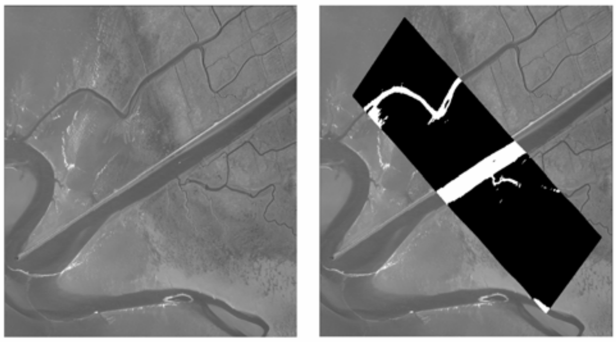

Figure 6: Classification of a part of a flight strip of the campaign “Friedrichskoog 2005” – left: lidar DTM, right: classified water points = white dots, classified land points = black dots

The used parameters, thresholds and weights are listed in Table 1. The thresholds of the parameters were obtained from training areas (see section 3.3) while the weights and the hysteresis-threshold-values were defined manually based on experience with the data set.

Table 1: Classification parameter of Example “Langeoog 2005” and “Friedrichskoog 2005”

	Langeoog 2005			Friedrichskoog 2005		
	Threshold		Weight	Threshold		Weight
	Water	Land		Water	Land	
Height [m]	-0.8	-0.4	2	1.4	2	3
Slope [°]	-10	10	1	-10	10	1
Intensity	---	---	0	22	40	1
Missed points	4	0	2	---	---	0
Segment length	2	10	2	---	---	0
Point density [point/m]	0.722	1.5	5	---	---	0
	low	**high**		**low**	**high**	
Water Threshold	(35%)	(50%)		(40%)	(50%)	

Table 2: Classification result of Example "Langeoog 2005" and "Friedrichskoog 2005"

	Langeoog 2005		Friedrichskoog 2005	
Number classified points	361.280		998.029	
Classified water points	121.399		86.991	
Classified land points	239.881		911.038	
	Water	**Land**	**Water**	**Land**
Classified water points	119.253	2.146	79.803	19.695
Classified land points	990	238.891	7188	891.343
Correctness [%]	99,2	99,1	91.7	97.8

To check the reached correctness the simultaneously acquired image data was merged into an orthophoto mosaic. Based on this mosaic the water and land area was digitized and intersected with the classified points. The results of the check are listed in Table 2. It can be seen that for "Langeoog 2005", the rate of correctly classified points within the land as well as the water is higher than 99%. The main border line between the sea and coast was nearly completely extracted. Only in the upper centre part of the flight strip the classification is not very accurate due to the fact that this part contains wet sand only slightly higher than the sea water level. The point density within the wet sand is significantly lower than in the neighboured dry sand area, thus the classification provides high water membership values for this part.

Also for "Friedrichskoog 2005", the results were very promising. 91.7% of the classified water points and 97.8% of the classified land points are correct. Analogous to the first example the algorithm has problems to classify wet land areas. Their intensity values are generally low and their height is only slightly higher than the neighboured water area.

5. CONCLUSION AND OUTLOOK

An approach to separate lidar points into the classes water and land based on 1D profile analysis of the raw lidar data has been introduced. The classification is based on the original lidar data and classifies for every flight strip. The algorithm uses several parameters which are derived from the lidar data. The classification is based on the fuzzy logic concept. Two different examples are shown to illustrate the capability of this algorithm. They point out that the classification algorithm is able to deliver accurate results for different lidar scanner types. However the classification lacks in accuracy if wet land area of low height occur.

In order to increase the automation rate it will be part of the future work to determine meaningful weights of the used parameter as well as the two final water thresholds from training areas.

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