SURFACE CLUSTERING FROM AIRBORNE LASER SCANNING DATA

Sagi Filin
Department of Geodesy, Faculty of Civil Engineering and Geosciences, Delft University of Technology, The Netherlands
s.filin@citg.tudelft.nl

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ABSTRACT

This paper presents an algorithm for the extraction of surface clusters from airborne laser data. Surface structure analysis is fundamental to almost any application involving LIDAR data, yet most algorithms focus only on identifying planar segments. The proposed algorithm is more general insofar as it aims at extracting surface segments that exhibit an homogeneous behavior, without restriction to one specific pattern. The algorithm adopts a data clustering methodology for this purpose, which offers a very general and flexible way to identify homogeneous patterns in the data.

1 INTRODUCTION

Laser altimetry has emerged in recent years as a leading technology for the extraction of information of physical surfaces. The dense description of physical objects and the terrain that is achieved by current airborne systems have led to an increased interest in utilizing the data for geospatial analysis as well as to surface reconstruction and terrain models generation. Growing experience shows, however, that the ability to use the raw data directly for deriving products and for analysis is rather limited, mainly as the data consists of a mixture of terrain, surface, and non-surface points without any semantic information that may distinguish one set of points from the others. As a result, applications that require separating one type of points from the others, e.g., masking vegetation, terrain points from non-terrain points, object points from non-object points, or applications that depend on evaluating local surface property require introducing some level of surface analysis to the data. It has been suggested to apply point based techniques as a potential solution to some applications, but experience shows that they have their own limitations and that a more rigorous approach is preferable. The role of surface structure analysis goes beyond filtering or masking the data. As digital surface models (DSM) generation, 3D object recognition, or applications such as 3D city modeling require laser surfaces as an input, laser surface analysis becomes prerequisite for any application that involves interpretation of the data. As laser surfaces are defined by laser points, identifying surface structure consists of grouping the points into segments with common attributes.

Segmentation of range data is still an active field. The majority of the reported algorithms concern close-range applications, as the works by, Besl (88); Köster and Spann (2000) or the review in Hoover et al. (1996), indicate. Yet, close range applications are usually applied to modeling objects with well-defined, smooth shapes; the surfaces surveyed by airborne LIDAR systems offer, in contrast, far more complex shapes representing a variety of natural phenomena. Notwithstanding, the majority of the reported algorithms focus on extracting planar surfaces (see, e.g., Lee and Schenk, 2001; Vosselman, 2001), mostly in association with the extraction of roof facets for building extraction. By narrowing their scope to this specific type of surfaces these algorithms are likely to fail with complex building shapes or with mixture of vegetation and buildings; they also lack the generality required in associating the laser points in the dataset with a segment (the essence of data segmentation). Based on similar arguments Maas (1999) and Oude Elberink and Maas (2000) tackle the segmentation of airborne laser data. The authors propose segmentation algorithms for a rasterized and quantized version of the range data. They identify classes in the data based on height texture measures. Their algorithms classify the data by attaching a label to each pixel but practically do not provide surface segments. So, while an association of the data with classes is achieved, identifying structure in the data is not guaranteed at all.

This paper presents a point clustering algorithm for extracting homogeneous segments in the laser data. Homogeneity refers to clusters of data sharing consistent attributes, and in the current case surface attributes. Clustering is a label for a variety of procedures aiming at grouping the data into homogeneous patterns, usually without an explicit a priori definition for the patterns. The clustering methodology offers generality and flexibility in accommodating spatial relation and attributes and also the ability to incorporate different cues into the process in a very natural way. Clustering can be seen as a combination of two processes – identifying patterns in the data based on attributes and grouping the data into clusters. Attributes should identify the properties that capture the sought-after information and produce the best separation among classes. Grouping concerns identifying areas with homogeneous attributes; the goal is to find clusters that are spatially meaningful and at the same time to avoid an algorithmic tendency for over-segmentation of the data. With laser data, further details regarding the data acquisition systems should be considered. The data itself consists by nature of a set of irregularly distributed points that carry only a limited amount of information, namely their x, y, and z coordinates. The spatial point distribution and the point density cannot be assumed fixed as they depend on the scanning system. The algorithm that is presented here copes with the varying point density and operates on the laser points directly without rasterization or other preliminary processing that may introduce unnecessary distortions. So, in addition to the algorithmic concerns, an adaptation of image-processing concepts to the irregular pattern becomes necessary. With the aim of identifying structure in the data in mind, the proposed algorithm is general and can be applied in a variety of applications.

2 SURFACE CLUSTERING

Similar to data segmentation, the goal of data clustering is to subdivide the data into disjoint regions each with a homogeneous property that distinguishes it from its surrounding. The regions are defined by the set of points included within each segment, where different regions cannot share points. The proposed algorithm considers the surface clusters an instantiations of more generic processes defined here as surface categories. The algorithm aims at distinguishing among four different surface categories, i) forested/wooded area, ii) low vegetation areas and rough surfaces iii) smoothly varying topography, and iv) planar surfaces. Surfaces refer here to the interpretation of the data obtained by laser scanning system, and the categories present one interpretation of the laser data surface. The surface classes are not aimed at providing a topographic structure of the terrain, mainly since the acquired data is not the terrain itself. Yet the clusters provide a separation of the surface into homogeneous parts. The distinction between smoothly varying topography and planar surfaces is made here because of the tendency of man-made object to have planar facets, and the value of this information to other applications.

2.1 The feature vector

By nature, laser data attributes will be derived from surface texture measurement.[1] The measures should be sufficient to differentiate among surface categories and among surfaces within each category. Several measures have been proposed for segmentation of range data, among them are the analysis of the height differences in a window via histogram followed by segmentation based on thresholding. Axelsson (1999) uses the second derivatives to find variations, and Maas (1999) uses a feature vector including the Laplace operator, maximum slope measures and the original height data in order to classify the data.

In this implementation clustering is performed based on an attribute vector consisting of the following measures – the point position, the parameters of the tangent plane to that point, and the relative height difference between the point and its neighbors. Together they form a 7-tuple vector $v_i := \{x_i, y_i, z_i, \vec{n}_{\{1,2\}i}, \rho_i, d_i\}$ for each point, with x_i, y_i, z_i, the laser point coordinates, $\vec{n}_{\{1,2\}i}, \rho_i$, the surface parameters (normal measured by two parameters and a constant), and d_i the height difference of the point to its neighbors.

The inclusion of the point position as an attribute is essential for measuring proximity to other points that share similar properties. Height differences are perhaps the most commonly used measures as they measure local variation and are expected to be reliable up to the level of noise in the data. They provide an adequate indication for the existence of high vegetation but they are insufficient for surface separation as the example in Figure 1 demonstrates. From an analytical standpoint height differences capture the existence of step edges in the data, and emulate the effect of an edge operator in raster data. Their main contribution is in enhancing the separation of clusters from one another. The tangent plane parameters consist of the normal direction and the constant. The slope parameters capture first-order discontinuities, thereby enhancing the separation of surface elements with different trend such as the ones in Figure 1. Slopes capture no positional information, but the constant value positions the plane in space and enables separating surfaces with similar slopes. Surface parameters and the height differences share some similarity; consider for example two horizontal planes for which the difference in the surface constant is in-fact the height difference. Yet, the plane constant refers to an infinite plane and is a rather global measure while the latter measures difference to a neighboring points, and is rather local.

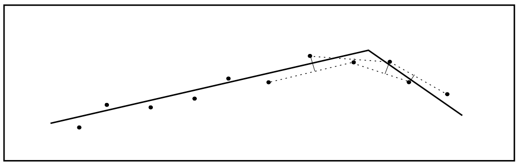

Figure 1: Potential inseparability of surfaces based on height differences

Category	Surface Slopes	Height Difference
High vegetation	Rapidly varying	Large
Low vegetation	Rapidly varying	Medium
Smooth surface	Locally constant	Small
Planar surface	Fixed	Small

Table 1: Surface categories vs. attributes

Table 1 lists the expected characteristics of these attributes for each of the four surface categories. The measures are qualitative and not strict, but they are sufficient to indicate that the chosen features make the identification of these four categories possible. Translating these measures into quantitative values is partially the essence of the algorithm.

2.2 Metrics to measure the attributes

Successful clustering of the data depends on the features representation. While height differences consist of a single measure and have a natural metric unit, planar surfaces can be described in various ways. It is common to use the explicit three parameters representation consisting of the slopes in the x and y direction, s_x, s_y and the intercept point. However, this representation breaks down with vertical or near vertical structures (e.g., walls.) The representation of the surface slopes by their tangents also offers

[1] If reflectance measurements are available, information can also be derived from these values.

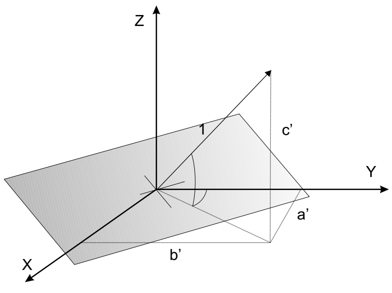

Figure 2: A plane in 3–D space

non-linear variations as the surface slopes increase. Measuring surface consistency may become then more difficult. With the implicit representation of a plane

$$0 = ax + by + cz + \rho \tag{1}$$

with a normalized normal vector $\parallel \vec{n} \parallel = 1$ (where $\vec{n} := \begin{bmatrix} a & b & c \end{bmatrix}^T$) any surface can be defined uniquely, but the non-linearity is still not solved and furthermore the dimensionality of the feature vector increases. Maintaining the three parameter representation and circumventing the non-linearity can be achieved by a polar representation of the surface normal. As is illustrated in Figure (2), with this representation the surface slopes angles can be computed as

$$\phi = cos^{-1}(c) \tag{2}$$

$$\theta = tan^{-1}\left(\frac{b}{a}\right) \tag{3}$$

The normal direction is then given by,

$$\vec{n} = R_z(\phi)\, R_y(\theta) \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} cos\theta cos\phi \\ sin\theta cos\phi \\ sin\phi \end{bmatrix} \tag{4}$$

leading to the polar representation

$$0 = cos\theta cos\phi\, x + sin\theta cos\phi\, y + sin\phi\, z + \rho \tag{5}$$

In this representation, ρ, is the distance from the origin to the plane. A plane is now defined by the angles, $\phi,\ \theta$ with angular units (radians or degrees), and ρ with a metric unit.

2.3 Surface texture analysis

Surface texture is usually analyzed by measuring the attributes variation in the neighborhood (usually a window) of each point and identifying the point's class by these measures. While point classification implicitly assumes homogeneous texture inside the window, that might not always be the case. For example, in inhomogeneous cases where different processes are covered by the window (e.g., around edges and building corners) erroneous surface classes will be assigned to the laser points. So, by assigning a class to each point this approach becomes rather restrictive in forming clusters in the data and relies heavily on the neighborhood size that is chosen.

The approach taken here is different. It is based on direct evaluation of the points features in a feature space with dimensions similar to the one of the feature vector; the values of the feature vector for each laser point determine the point's coordinate in the feature space. Data clustering is conducted in this space via unsupervised classification. Notice that by analyzing all the points simultaneously no window based analysis is needed at all, in fact all windows are analyzed simultaneously. To accelerate the clustering of the data the implementation of the algorithm here partitions the feature vector into a 4D attribute space consisting of the tangent plane parameters and the height differences, and the 3D point position in object space. The removal of the positional content does not allow for establishing proximity measures in the feature space. The clusters in this space can only be considered as "surface classes" that contain all of the points that share similar features. Table 1 shows that the attributes are sufficient for extracting distinct surfaces classes, but a surface class may consist of more than one point cluster in object space. Thus, following the surface class extraction, point clusters are identified in object space by proximity measures. The current implementation uses a topological neighborhood that is established by the triangulation of the dataset as a measure. Smooth surfaces tend to cluster in the attribute space but "vegetation" surfaces (categories (i) and (ii) in Table 1) do not. Rough or "vegetation" surfaces are defined by their lack of consistency, and are identified by analyzing the unclustered points. The surface attributes that are used here, in particular the surface normals, enhance the tendency of vegetation not cluster. One consequence is that vegetation and structured surfaces are unlikely to be grouped together. Clustering the "vegetation" points is carried out by analyzing the "unstructured" points. The separation between high vegetation and low vegetation is conducted by analyzing the points according to their height difference and graph connectivity, although in mixed areas such separation may not be possible.

2.3.1 Relation to other parameter-space based representations

As the tangent plane parameters are the key feature in identifying surface structure (height differences are mostly used to eliminate edge points from the analysis) one may associate this representation and the Hough-transform for planar surfaces. In reality, this similarity is rather limited but the comparison enables illuminating some properties of the current representation. The Hough transform (see details in Vosselman, 2001, for example) is optimal for grouping data that have no connectivity, for example the set of all points that form together a line, or in this case a plane. However, connectivity between points is one of the more important attributes of the sought after surface elements. By identifying surface of unconnected points the Hough transform generates proposals for many spurious planes that do not exist in reality. With the increase of the size of the dataset that is processed the number of spurious surfaces will increase rapidly. The extraction of real surface from the Hough space will become complex and slow, and identifying physical surfaces with a relatively small number points will become more difficult. The current, feature based representation, computes attributes locally with the goal of finding points that share similar attributes, so the odds of finding a significant number of points that share similar attributes but are not connected are low. The local computation of the attributes also suggests that this method is largely independent of the volume of data that is analyzed, an increase in the size of the dataset has only little effect on the number of spurious surfaces. In addition, as surface classes are identified by grouping points with similar surface parameters, the clustering algorithm can support the extraction of smooth surface and not only planar ones, a feature that cannot be achieved by the Hough representation. Comparing the feature space based approach to region-growing based segmentation shows that there is no dependency here on the selection of seed-points in this implementation. This is another merit of this approach, structure is obtained directly from the parameter space.

3 THE CLUSTERING ALGORITHM

The clustering algorithm consists of three main processes – generation of cluster proposals, validation, and refinement. Based on the formation of the feature space the clustering algorithm can be described as follows

1. initialize n_{min} the minimal number of points per cluster and s_{max} an accuracy threshold
2. compute attributes d_i and $\vec{n}_{\{1,2\}i}, \rho_i$ $\forall$ laser points
3. generate a feature space
4. propose a surface class and identify points associated with the class
5. group points according to the neighborhood system
6. **for** each group
7. **if** group size $\leq n_{min}$ **then** dismiss group **else**
   compute surface attributes for the group in particular the estimated standard deviation s
8. **if** $s > s_{max}$ **then**
9. Test for the existence of outliers
10. Test for the existence of more than one class and split if needed
11. **endfor**
12. **repeat** steps 3–10 **until** no meaningful surfaces are proposed
13. Extend each cluster based on its attributes **until** no further points can be added, or another cluster was reached
14. Merge clusters that share similar attributes and test for surface model
15. Analyze and group unclassified points based on height variation

The computation of the features is governed in large by the existence of noise and outliers in the data, which may distort the feature values and thereby affect the analysis of the parameter space and the clusters. Outliers are identified as points that statistically do not belong to their surrounding. Analysis is performed here by t-test. The term outlier may be misleading since some of these points are in fact reflected from physical objects (e.g., power lines or poles). Notice that by computing the attributes based on the point neighborhood the computation becomes a geometric implementation of a low-pass filter integrated into the computation of the first derivatives.

Surface clusters are derived by the extraction surface classes and grouping the points in object space. Many unsupervised classification algorithms can suit for the extraction of surface classes; the one that was implemented here is based on a mode seeking algorithm, which does not require predefining the number of clusters such as in many other unsupervised classification methods. A mode seeking algorithm is better suited for identifying planar surface elements, therefore planar surface fitting is used for validation of surface cluster. In case of a large cluster and inadequate plane fitting results a smooth surface model is tested as well; the determination of the actual surface shape (planar or smooth) is done at a later stage. The validation concerns testing whether the cluster is homogeneous and indeed composed of only one surface class; and if that is the case, validating that all points in the cluster belong to the same class. It is possible (and happens indeed) that due to smoothing, points that do not belong to the class (or that are marginal) obtain attributes similar to their neighbors. The algorithm handles the two scenarios as follows. The null-hypothesis assumes that the cluster represent only one class. Therefore, the existence of outliers is tested first. The implementation of outlier detection is carried out by an analysis of the normalized residuals. Instead of the standard deviation the median deviation, a measure that is more robust to the existence of outliers is used. Indeed, robust methods for detection of up to 50% outliers, like the least-median-of-squares (Rousseeuw and Leroy, 1987), exist. But as they are essentially greedy algorithms they are very slow. The current situation is by the nature of the process more controlled, and leads to the simplified algorithm to work well. Its failure is an indication that the cluster may be composed of more than on surface. Testing for the existence of more than one surface is implemented here by tuning the clustering to the given set of points.

The cluster refinement phase involves extending the cluster by collecting points that were not identified first as part of the cluster, and then merging clusters that are part of the same surface. Extension of the cluster to neighbor points is only a natural step, usually the cluster constructed by the feature space will not include boundary points. Inclusion of points is done by testing whether the point is from the same distribution as the cluster is. Points along crease edges may be associated with several neighboring surfaces, they are marked as ambiguous points. The merging of clusters is decided upon testing whether the clusters share similar mean (which are the estimated surface parameters) and

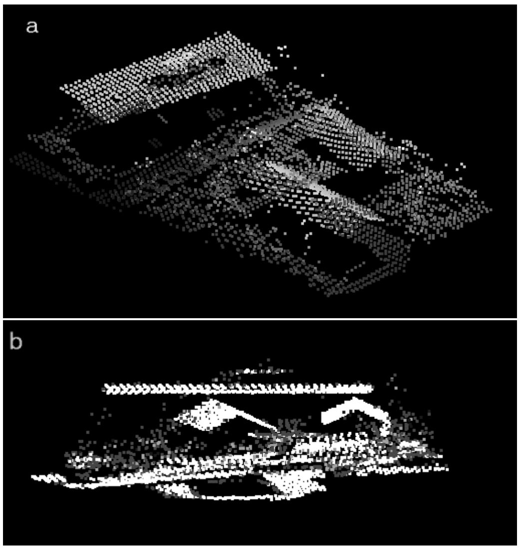

Figure 3: Clustering results for Stuttgart data (1.5m resolution). a.) the original range data, b.) The clustered data. Bright points – part of a smooth or planar surface, gray points – vegetation points or ones with high elevation variation.

standard deviation. The merging part involves also testing the surface model. The preference is for simple description of the surface, so if both surface elements are planar, then merging into one planar surface is tested first; if this test fails the following test analyzes if both surface elements are part of one smooth surface. Smooth surfaces are modeled here as biquadratic surfaces. Notice that this way an extension to other surface models can be incorporated in a very straight-forward way.

The size of the segments is controlled by the standard deviation thresholds that are being set. In addition to the upper limit s_{max} a lower bound limit, s_{min} is also set to avoid undersegmentation. The value is set in accordance with the expected accuracy of the laser points themselves. When a segment is extended and its *std.* is below the minimum threshold, s_{min} is used instead. Using the fitting accuracy as the measure to evaluate clusters offers a very natural way to control a cluster, and the use of lower threshold is another way to encourage bigger clusters. The preference of planar surfaces in the merging phase and the establishing of upper and lower bounds for the *std.* of the parameterized surface enables avoiding over- and undersegmentation of the data, as well as overparameterization of a surface.

4 DISCUSSION AND RESULTS

Results for testing the algorithm are presented for datasets with medium to relatively low resolutions, which are less detailed and considered more difficult to process. The first dataset is taken in the Stuttgart area. The spacing is about 1.5 m between points. The scene contains several buildings, smooth ground surface and vegetation that is close to the buildings. The dataset is presented in Figure 3.a and

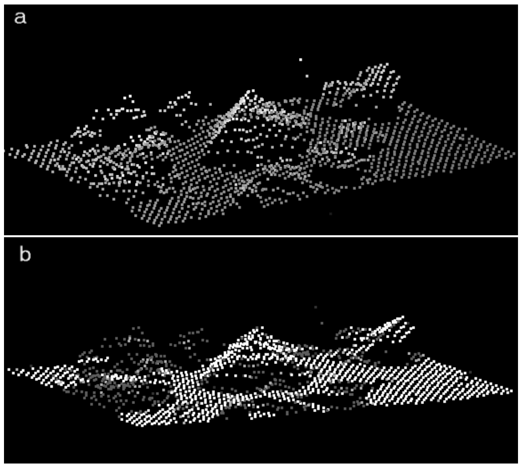

Figure 4: Clustering results for Vahingen data (2.5m resolution). a.) the original range data, b.) the clustered data. Bright points – part of a smooth or planar surface, gray points – vegetation points or ones with high elevation variation.

the results of applying the clustering algorithm are in Figures 3.b. Bright points are part of a smooth surface, gray ones are part of a vegetation or unclassified points with high elevation variation. As can be seen, the algorithm managed to separate successfully the smooth objects, like roof tops or smooth parts on the ground, from the vegetation, even in cases were both were close one to the other. Since the vegetation is rather sparse it is difficult to distinguish between high and low vegetation. Therefore, they are classified as one structure.

The second dataset has a lower ground spacing of about 2.5m between points. The dataset is acquired over the Vahingen area in Germany. Buildings here are smaller in size and lower in height; therefore, finding structure like planar surfaces is more difficult. The results show that the algorithm managed to identify successfully the facets of the building at the center of the scene and also the one at the far right. Considering the complexity of the shape of the central building and the point spacing, the results indicate that the algorithm is capable of identifying fine structures without any preliminary knowledge of their location. The algorithm does not favor, however, identifying structure when one does not exit as the mostly correct classification of the vegetation indicate.

The final example is a natural terrain with heavy vegetation taken from the Stuttgart dataset. The vegetation consists mainly of wooded area over a side of a hill. Down the hill by the vegetation, a roof face can be noticed and then a part of a road. The results of the clustering algorithm are given in Figure 5. The algorithm has managed to separate the surface from the vegetation successfully, to identify the roof facets and to find ground segments on the sloping terrain wherever they formed a significant segment.

The quality of the clusters is analyzed, for the first two datasets, by the standard deviation of the laser points from the fitted surface. The minimal size of clusters was set

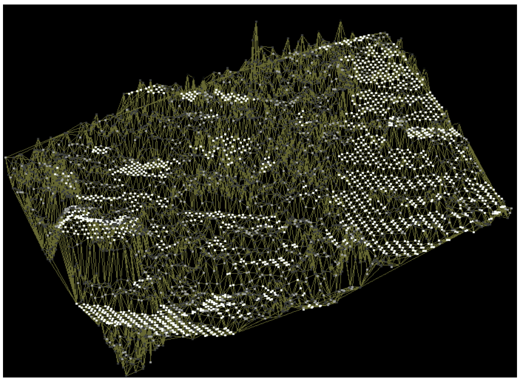

Figure 5: Clustering results for vegetated area in the Stuttgart data overlaid on mesh of the data. Bright points – smooth or planar surface, gray points – vegetation points.

Dataset	*std.* range [m]	number of clusters [%]
Stuttgart	$0 < s < .05$	61
	$0.05 < s < .10$	38
	$0.10 < s < .12$	1
Vahingen	$0 < s < .05$	60
	$0.05 < s < .10$	34
	$0.10 < s < .12$	6

Table 2: Accuracy estimate of the surfaces clusters

to seven points, which offers redundancy of four point in plane fitting, and also refers to the point density and the size of objects in the Vahingen dataset (in particular roof faces). Results are summarized in Table 2. The quality of the results is an indication to the potential quality of information that can be achieved by LIDAR data. As can be seen from Table 2 in both cases the majority of the clusters had a *std.* smaller than 5 cm, which was the minimum threshold that was set. In both cases a small fraction of clusters had a *std.* larger then 10 cm but did not exceed 13 cm even though the upper limit was set to 15 cm. The results indicate that the cluster proposals manage to propose natural clusters. The surface fitting accuracy of the large clusters within all three datasets was below 5 cm. The size of the large clusters was on the order of several hundred of points per cluster. The majority of the clusters in the high-accuracy category had a relatively large number of points per cluster. There is a high similarity between the number of points per cluster and surface quality, so in addition to the data density the number of points has an effect on the ability to determine the surface parameters accurately. This realization was very evident in the Vahingen dataset, where few of the roof faces clusters had their fitting accuracy in the third category ($10\,\mathrm{cm} < std. < 12\,\mathrm{cm}$), without much place for improvement by removing points. It was evident that these points represent a structure, as they all were part of one roof face, so dismissing them seemed a wrong decision. As these objects are very likely to represent a structure in the data that due to low point density cannot be defined more precisely, these points are considered as a coarse representation of these objects. The *std.* value that is attached to these clusters serves as an indication for that.

5 CONCLUSIONS

The paper presented a methodology for clustering laser data surfaces. As a first step surface categories were defined; the categories present one way to interpretation of the surface. Features that enable distinguishing among these categories and among surfaces within each category were defined and a way to measure them was developed. Following the definition of the features a method for modeling surface texture in the data was derived, and the clustering algorithm was established. The approach that is taken does not require defining windows to identify surface texture in the data and does not require limiting the data volume that is processed. The interaction between the parameter space and object space, and the validation phase relaxes the dependency of parameters that are determined within the algorithm, and makes the process more robust to the existence of errors. The results show that even with relatively sparse datasets, structure can be identified alluding to the generality of the algorithm.

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