EVALUATING THE POTENTIAL OF CLUSTERING TECHNIQUES FOR 3D OBJECT EXTRACTION FROM LIDAR DATA

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Abstract: During the last decade airborne laser scanning (LIDAR) has become a mature technology which is now widely accepted for 3D data collection. Nevertheless, these systems have the disadvantage of not representing the desirable bare terrain, but the visible surface including vegetation and buildings. To generate high quality bare terrain using LIDAR data, the most important and difficult step is filtering, where non-terrain 3D objects such as buildings and trees are eliminated while keeping terrain points for quality digital terrain modelling. The main goal of this paper is to investigate and compare the potential of procedures for clustering of LIDAR data for 3D object extraction. The study aims at a comparison of K-Means clustering, SOM and Fuzzy C-Means clustering applied on range laser images. For evaluating the potential of each technique, the confusion matrix concept is employed and the accuracy evaluation is done qualitatively and quantitatively.

1 INTRODUCTION

In recent years LIDAR data has become as a highly acknowledged data source for interactive mapping of 3D man-made and natural objects from the physical earth's surface. The dense and accurate recording of surface points has encouraged research in processing and analysing the data to develop automated processes for feature extraction, object recognition and object reconstruction. However, the algorithm for segmentation of this kind of data, i.e. distinguish between ground surface and objects on the surface, is still on going researched (Haala and Brenner 1999; Axelsson, 1999; Maas and Vosselman, 2001).

Nowadays, laser-scanning systems are able to collect of two different types from the ground surface and the objects over it; first-pulse and last-pulse data. Laser pulses have one important advantage that partially they penetrate the vegetation in gaps between leaves and obtain data reflected from points underneath the vegetation. This property of the laser defines the difference between first- and last- pulse data. That means in first-pulse data, the data of the vegetation's surface is available, while it is not the case in last-pulse. The other main property of laser scanning systems is the ability to provide the range data from the objects in addition to the reflectance image data (intensity data). This range data obtained from the elevation points over the earth's surface or other 3D objects can be converted to a digital range image. Therefore the laser scanners, nowadays, can provide both range image and intensity image in two different types, first- and last-pulse data (Sithole, 2003; Roggero, 2002).

The paper shows the potential of the analysis of height texture for the automatic segmentation of LIDAR regular range datasets and 3D objects extraction in the segmented data. Based on the definition and computation of a number of texture measures used as bands in three clustering approaches (i.e. K-Mean, FCM and SOM), 3D objects like buildings and trees can be recognized from bare terrain.

2 CLUSTERING OF LIDAR DATA

Cluster analysis is a difficult problem because many factors (such as effective similarity measures, criterion functions, algorithms and initial conditions) come into play in devising a well tuned clustering

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technique for a given clustering problem. Cluster analysis is an unsupervised learning method that constitutes a cornerstone of an intelligent data analysis process. It is used for the exploration of inter-relationships among a collection of patterns, by organizing them into homogeneous clusters. It is called unsupervised learning because unlike classification (known as supervised learning), no a priori labeling of some patterns is available to use in categorizing others and inferring the cluster structure of the whole data. Intra-connectivity is a measure of the density of connections between the instances of a single cluster. A high intra-connectivity indicates a good clustering arrangement because the instances grouped within the same cluster are highly dependent on each other. Inter-connectivity is a measure of the connectivity between distinct clusters. A low degree of interconnectivity is desirable because it indicates that individual clusters are largely independent of each other.

K-Means: The most well-known partitioning algorithm is the K-Means (Rottensteiner and Briese, 2002). The K-Means method partitions the data set into *k* subsets such that all points in a given subset are closest to the same centre. In detail, it randomly selects *k* of the instances to represent the clusters. Based on the selected attributes, all remaining instances are assigned to their closer centre. K-Means then computes the new centres by taking the mean of all data points belonging to the same cluster. The operation is iterated until there is no change in the gravity centres. If *k* cannot be known ahead of time, various values of *k* can be evaluated until the most suitable one is found. The effectiveness of this method as well as of others relies heavily on the objective function used in measuring the distance between instances. The difficulty is in finding a distance measure that works well with all types of data.

FCM: Traditional K-Means clustering approaches generate partitions; in a partition, each pattern belongs to one and only one cluster. Hence, the clusters in a hard clustering are disjoint. Fuzzy clustering extends this notion to associate each pattern with every cluster using a membership function. Larger membership values indicate higher confidence in the assignment of the pattern to the cluster. One widely used algorithm is the Fuzzy C-Means (FCM) algorithm, which is based on K-Means. FCM attempts to find the most characteristic point in each cluster, which can be considered as the "centre" of the cluster and, then, the grade of membership for each instance in the clusters.

Let us assume as a Fuzzy C-Means Functional where, $Y = \{y_j \mid j \in [1,c]\}$ is the set of centers of clusters; $E_j(x_k)$ is a dissimilarity measure (distance or cost) between the sample x_j and the center y_j of a specific cluster *j*; $U = [u_{jk}]$ is the $c \times n$ fuzzy c-partition matrix, containing the membership values of all samples in all clusters; $m \in [1,\infty)$ is a control parameter of fuzziness.

$$J_m(U,Y) = \sum_{k=1}^{n} \sum_{j=1}^{c} (u_{jk})^m E_j(x_k) \quad (1)$$

The clustering problem can be defined as the minimization of J_m with respect to *Y*, under the *probabilistic constraint*:

$$\sum_{j=1}^{c} u_{jk} = 1 \quad (2)$$

The Fuzzy C-Means algorithm consists in the iteration of the following formulas:

$$y_j = \frac{\sum_{j=1}^{c} (u_{jk})^m x_k}{\sum_{k=1}^{n} (u_{jk})^m} \quad \text{for all } j, \quad (3)$$

$$u_{jk} = \begin{cases} \left(\sum_{l=1}^{c} \left(\frac{E_j(x_k)}{E_l(x_k)} \right)^{2/m-1} \right)^{-1} & \text{if } E_j(x_k) \rangle 0 \quad \forall j,k \\ 1 & \text{if } E_j(x_k) \text{ and } u_{lk} = 0 \quad \forall l \neq j \end{cases}$$

Where, in the case of the Euclidean space:

$$E_j(x_k) = \|x_k - y_j\|^2 \quad (4)$$

SOM: Among the other types of artificial neural networks, the self organizing neural network resembles real biological neural networks more than the other types. It was first introduced by Kohonen (Kohonen, 1989) as the "Self Organizing Feature Map". SOM can be seen as an extension to the competitive learning neural network. In the SOM, the output units are ordered in some fashion, often in a two dimensional grid or array. The ordering of output units determines which neurons are neighbours.

When learning patterns are presented to the SOM, the weights to the output neurons are thus adapted such that the order present in the input space is preserved in the output space. This means that learning patterns which are near to each other in the input space must be mapped on output units which are also near to each other.

SOM can be described step by step as follows:

1. Random Initialization of neurons weights (W_{ij}), where i and j are the identifiers of the input and output neurons, respectively.
2. Introduce randomly selected learning pattern (Pj) to the network. Compute the dissimilarity between input pattern and all neurons in the output layer of SOM and determine the winner (closest) neuron, using the Euclidean distance, where p_j^n is the input to neuron i at iteration n.

$$d_i^2 = \sum_{j=1}^{f} \left(P_j^n - w_{ij}^n\right)^2 \quad (5)$$

$$S = max\ (d_i) \quad (6)$$

3. Find winner neuron neighbours using defined neighbourhood function.
4. Update the weights of winner and its neighbours, using Hebbian learning rule.

$$w_i^{n+1} = w_i^n + \alpha^n \cdot N_{i'} \cdot \left(P_{ij}^n - w_i^n\right) \quad (7)$$

using Eq. (7) α^n denotes the learning rate in the iteration n expressed as below and $N_{i'}(\gamma^n)$ is the neighbourhood function of the winner neuron i'.

$$\alpha^n = \frac{\alpha_0}{1+100\,n/T} \qquad 0 \le \alpha_0 \le 1 \quad (8)$$

5. Repeat step 1 to 4, until network converges.
6. Introduce all patterns to the network.
7. Find winner neuron for each input pattern.
8. Assign presented pattern to the cluster which winner neuron points to it.

2.1 Clustering Validity Checking

Clustering is perceived as an unsupervised process since there are no predefined classes and no examples that would show what kind of desirable relations should be valid among the data. As a consequence, the final partitions of a data set require some sort of evaluation in most applications (Kohonen, 1989). For instance questions like "how many clusters are there in the data set?", "does the resulting clustering scheme fits our data set?", "is there a better partitioning for our data set?" call for clustering results validation and are the subjects of a number of methods discussed in the literature. They aim at the quantitative evaluation of the results of the clustering algorithms and are known under the general term cluster validity methods.

The procedure of evaluating the results of a clustering algorithm is known under the term *cluster validity*. In general terms, there are three approaches to investigate cluster validity. The first is based on *external criteria*. This implies that we evaluate the results of a clustering algorithm based on a pre-specified structure, which is imposed on a data set and reflects our intuition about the clustering structure of the data set. The second approach is based on *internal criteria*. We may evaluate the results of a clustering algorithm in terms of quantities that involve the vectors of the data set themselves (e.g. proximity matrix). The third approach of clustering validity which we used in our research work is based on *relative criteria*.

Here the basic idea is the evaluation of a clustering structure by comparing it to other clustering schemes, resulting by the same algorithm but with different parameter values. There are two criteria proposed for clustering evaluation and selection of an optimal clustering scheme:

1- *Compactness*, the members of each cluster should be as close to each other as possible. A common measure of compactness is the variance, which should be minimized.

2- *Separation,* the clusters themselves should be widely spaced. There are three common approaches measuring the distance between two different clusters:
Single linkage: It measures the distance between the closest members of the clusters.
Complete linkage: It measures the distance between the most distant members.
Comparison of centroids: It measures the distance between the centers of the clusters.
The two first approaches are based on statistical tests and their major drawback is their high computational cost. Moreover, the indices related to these approaches aim at measuring the degree to which a data set confirms a-priori specified scheme. On the other hand, the third approach aims at finding the best clustering scheme that a clustering algorithm can be defined under certain assumptions and parameters.

A number of validity indices have been defined and proposed in literature for each of above approaches (Halkidi *et al.*, 2001). The indices which are used in this paper are the Davies-Bouldin (DB) index and Hubert index.

Davies-Bouldin index: A similarity measure R_{ij} between the clusters C_i and C_j is defined based on a measure of dispersion of a cluster C_i and a dissimilarity measure between two clusters d_{ij} (Davies and Bouldin, 1979). One choice for R_{ij} that satisfies the above conditions is:

$$R_{ij} = (s_i + s_j)/d_{ij} \quad (9)$$

Then the DB index is defined as:

$$DB_{nc} = \frac{1}{nc}\sum_{i=1}^{nc} R_i \qquad (10)$$

$$R_i = \max\{R_{ij}\} \quad i=1, \ldots, n_c \quad i \neq j$$

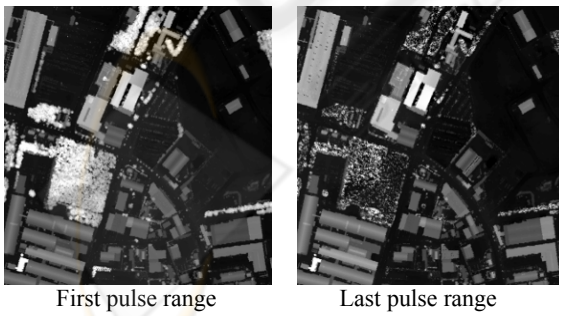
It is clear for the above definition that DB_{nc} is the average similarity between each cluster and its most similar one. It is desirable for the clusters to have the minimum possible similarity to each other; therefore we seek clustering that minimizes DB. The DB_{nc} index exhibits no trends with respect to the number of clusters and thus we seek the minimum value of DB_{nc} in its plot versus the number of clusters.

Hubert Index: The definition of the Hubert Γ index (Hubert, 1985) is given by the Eq. (11) where N is the number of objects in a dataset, $M=N(N-1)/2$, P is the proximity matrix of the data set and Q is an $N \times N$ matrix whose (i,j) element is equal to the distance between the representative points (v_{ci}, v_{cj}) of the clusters where the objects x_i and x_j belong.

$$\Gamma_m^H = \frac{1}{M}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} P(i,j)Q(i,j) \qquad (11)$$

3 EXPERIMENTS AND RESULTS

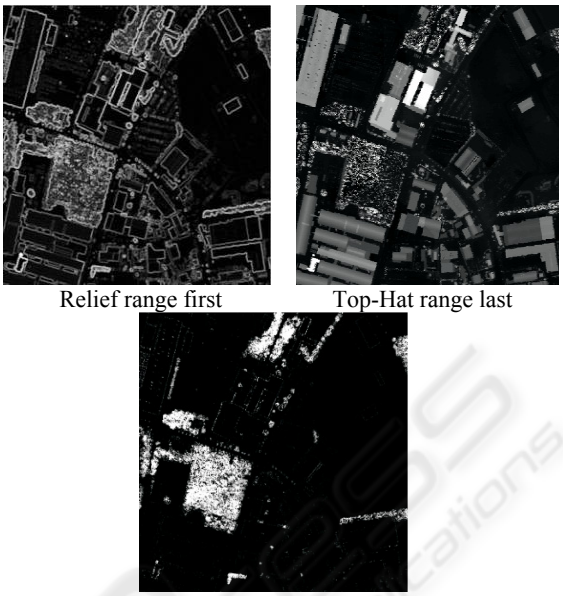
The airborne LIDAR data used in the experimental investigations have been recorded with TopScan Airborne Laser Terrain (TopScan, 2004). The average density of the measured 3D points is about *1.7* per m^2. Figure 1 shows the first-pulse and the last-pulse LIDAR range image from the city of Rheine in Germany. The impact of the Vegetation in the first- and last- pulse images can be easily recognized by comparing the two images of this figure.



First pulse range Last pulse range

Figure 1: LIDAR dataset.

The first step in every clustering process is to extract the feature image bands. The features of theses feature bands should carry useful textural or surface related information to differentiate between regions related to the surface.



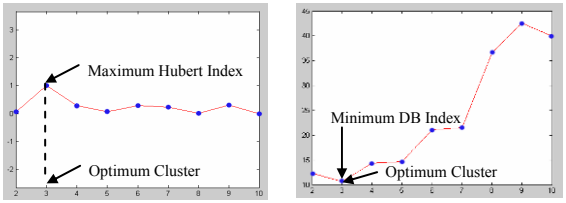
Relief range first Top-Hat range last

NDVI range

Figure 2: Three applied Feature.

Several features have been proposed for clustering of range data. Axelsson (1999) employs the second derivatives to find textural variations and Maas (1999) utilizes a feature vector including the original height data, the Laplace operator, maximum slope measures and others in order to classify the data. In our work, three types of features are taken into account. These features are: NDDI ratio, Morphological Opening and relief of range information of LIDAR data. Figure 2 shows the output of three mentioned features on LIDAR data set.

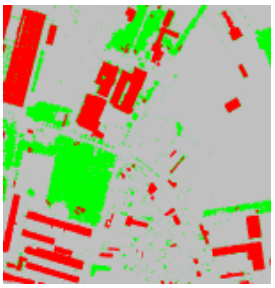
To assess the validity of clustering algorithm we experimented the algorithm for $n_c = 1$ to $n_c = 10$. Using Davies-Bouldin (DB) and Hubert indices, three clusters are optimum according to input data. Plot of the indices versus n_c is depicted in Figure 3.



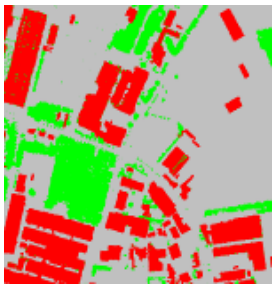
Hubert Index DB Index

Figure 3: Optimum Clusters.

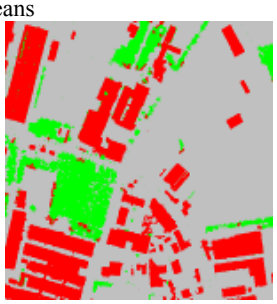
Figure 4 shows outputs of the K-Mean, FCM and SOM algorithms for the situation of optimum cluster number (i.e. 3).



K-Means

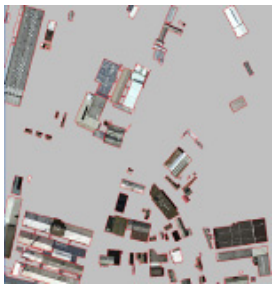


SOM

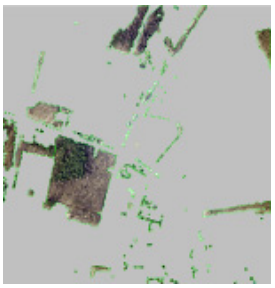


FCM

Figure 4: The situation of optimum cluster number.



Man-made objects



Vegetation

Truth Data

Figure 5: The truth data.

4 ANALYSIS OF CLUSTERING RESULTS

After performing clustering algorithms (K-Means, FCM and SOM), it is necessary to assess their accuracies. In this context, the term accuracy means the level of agreement between labels assigned by the clustering algorithm and class allocation based on truth data. To generate an appropriate truth data, we used aerial image of the scene and first-pulse range of LIDAR data. Using these data we produced the ortho-image. Then, Buildings and vegetation have been digitized, manually. Figure 5 shows the truth data.

The method used in this paper to assess the accuracy of clustering results is based on analysis of the confusion matrix. The most common tool for the clustering accuracy assessment is in term of a confusion matrix. The columns in a confusion matrix represent truth data, while rows represent the labels assigned by the clustering algorithm. The confusion matrix of K-Means, FCM and SOM results, are presented in Table 1, respectively.

Several indices of clustering accuracy can be derived from the confusion matrix. One of these indices is "overall accuracy", which is obtained by dividing the sum of main diagonal entries of the confusion matrix by the total number of patterns. Figure 6 shows the "overall accuracy" of K-Means, FCM and SOM.

Table 1: Confusion matrix of K-Means, FCM and SOM.

		Truth Data			
K-Means		Buildings	Vegetation	Bare-Land	Sum
	Buildings	64338	1551	338	66227
	Vegetation	3561	58692	5930	68183
	Bare-Land	54341	10509	290740	355590
	Sum	122240	70752	297008	490000
FCM		Buildings	Vegetation	Bare-Land	Sum
	Buildings	108835	4292	1697	114824
	Vegetation	921	49488	517	50926
	Bare-Land	12484	16972	294794	324250
	Sum	122240	70752	297008	490000
SOM		Buildings	Vegetation	Bare-Land	Sum
	Buildings	116002	591	4666	121259
	Vegetation	2224	63953	3344	69521
	Bare-Land	4014	6208	288998	299220
	Sum	122240	70752	297008	490000

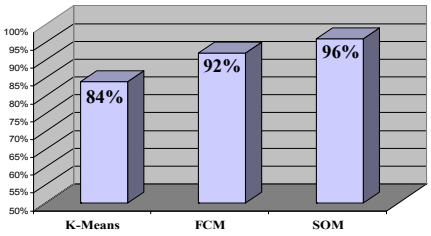


Figure 6: Overall accuracy of K-Means, FCM and SOM.

The accuracy measurements shown above, namely, the overall accuracy and producer's accuracy, though quite simple to use, are based on either the principal diagonal or columns of confusion matrix only, which does not use the information from the whole confusion matrix. A multivariate

index called the kappa coefficient (Cohen, 1960) has found favour. The kappa coefficient is defined as Eq. (12) where k is number of clusters, M_{i+} and M_{+i} are the marginal totals of row i and column i, respectively and N is the total number of patterns.

$$\kappa = \frac{N \cdot \sum_{i=1}^{k} M_{i,i} - \sum_{i=1}^{k} (M_{i+} \cdot M_{+i})}{N^2 - \sum_{i=1}^{k} (M_{i+} \cdot M_{+i})} \quad (12)$$

Figure 7 shows the "kappa coefficient" of K-Means, FCM and SOM.

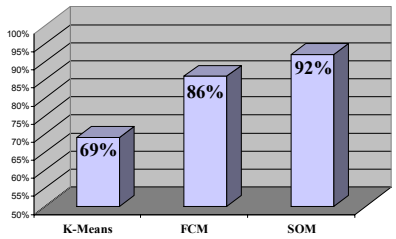


Figure 7: Kappa coefficient of K-Means, FCM and SOM.

The value of kappa for each cluster can be derived as follows:

$$\kappa_i = \frac{N \cdot M_{i,i} - M_{i+} \cdot M_{+i}}{N \cdot M_{i+} - M_{i+} \cdot M_{+i}} \quad (13)$$

5 CONCLUSION

Airborne laserscanning is being used for an increasing number of mapping and GIS data acquisition tasks. Besides the original purpose of digital terrain model generation, new applications arise in the automatic detection and modeling of objects such as buildings or vegetation for the generation of 3-D city models. A crucial prerequisite for the automatic extraction of objects on the Earth's surface from LIDAR height data is the clustering of datasets. Besides the height itself, height texture defined by local variations of the height is a significant feature of objects to be recognized.

We have presented the results of applying three different clustering techniques on LIDAR data for 3D object extraction. Using these methods we have been able to filter non-terrain 3D objects such as buildings and trees while keeping terrain points for quality digital terrain modelling.

However, as it appear from obtained results of applying different clustering methods on LIDAR data; the SOM has the most reliable potential for extraction of 3D objects like building and trees from bare terrain.

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