LIDAR Data Classification using Hierarchical K-means clustering

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ABSTRACT:

This paper deals with lidar point cloud filtering and classification for modelling the Terrain and more generally for scene segmentation. In this study, we propose to use the well-known K-means clustering algorithm that filters and segments (point cloud) data. The K-means clustering is well adapted to lidar data processing, since different feature attributes can be used depending on the desired classes. Attributes may be geometric or textural when processing only 3D-point cloud but also spectral in case of joint use of optical images and lidar data. The algorithm is based on a fixed neighborhood size that can deal with steep relief covered by dense vegetation, mountainous area and terrains which present microrelieves. The novelty of our algorithm consists in providing a hierarchical splitting clustering to extract ground points. The number of cluster splits is used to qualify automatically the classification reliability. This point is rarely treated in previous works. Moreover landscape predictors such as slope map are used to locally refine the classification. Finally, the methodology is extended to a multiscale framework. The hierarchical clustering is processed from coarse DTM resolution to finer one. This implementation improves the algorithm robustness and ensures reliable ground estimation. Quantitative and qualitative results are presented on the ISPRS data set.

1 INTRODUCTION

Representing the Earth's topography, that is the vegetation, the true terrain, buildings as well as any human-made infrastructures from aerial remote sensors in a 3D virtual environment has been a challenging task for scientists for many years. Recent years have seen the development of airborne scanner systems which provide dense 3D point cloud of the surface topography. This massive amount of data has to be analyzed and classified to extract pertinent informations. A Digital Terrain Model (DTM) is a fundamental layer for any application in a 3D virtual environment, and as a matter of course, plays a main role when dealing with natural risk management. Several methods have been developed for filtering lidar data to generate Digital Terrain Models. Algorithms have to process large data volumes on various and complex landscapes such as urban areas Dell'Aqua et al. (2001), forest areas Kraus and Pfeifer (1998); Haugerud and Harding (2001) or mountainous areas Wack and Stelzl (2005). Many algorithms have been implemented and tested so far, but no generic solution appeared Sithole and Vosselman (2003). Existing works on lidar data labelling can be divided into three major approaches that will be briefly detailed hereby:

1. **Morphological filters** These filters are based on a series of 3D morphological closings and openings. Robust methods against measurement errors were proposed using a dual rank filter Eckstein and Munkelt (1995). The filter parameters highly depend on the terrain slope as well as on the relevancy of laser points to belong to the terrain: last pulse is not always a true ground point, especially in presence of dense vegetation coverage. Vosselman (2000); Sithole (2001) proposed a slope based filtering. In Kraus and Pfeifer (1998), authors have proposed an iterative linear prediction scheme to remove vegetation points in forest areas. The potential of morphological filters to provide a good estimate of the ground depends on the filtering window size. A small window size leads to a fine local topography provided that there are enough true ground points within the neighborhood. On the contrary, a large window size tends to smooth the final DTM. To overcome these effects, some authors refine locally the window size of the filter Kilian et al. (1996); Bretar and Chehata (2007). Zhang et al. (2003) have used an iterative technique using progressive morphological filters by varying the window size to estimate different height thresholds in local regions. Others propose a repetitive interpolation of DTM in forest areas Filin and Pfeifer (2006); Kobler et al. (2007) to improve the algorithm robustness. The advantage of the morphological filters is the short computing time but they need an accurate a-priori knowledge about the terrain topology.

2. **Progressive TIN densification** Some points are identified as ground points and based on those, new points will be added to the ground class Sohn and Dowman (2002). In Axelsson (2000), the authors present an iterative Triangular Irregular Network generation. From a coarse triangulated surface based on the lowest points, new lidar points are integrated in a Delaunay triangulation under strong angle and distance constraints. The advantages of triangulation based methods are the short computing time and the robustness. However, the TIN surface is very sensitive to negative outliers that may shift the surface downwards.

3. **Surface model filters** These filters are based on robust interpolation of ground points Kraus and Pfeifer (1998). A coarse surface is estimated. All points are weighted by a power function of their residuals to the approximated surface. The surface converges toward points with negative residuals. In Elmqvist (2002), the ground is estimated by an active shape model. The drawback of this approach is that it is controlled with many parameters and is sensitive to negative outliers.

In addition to the filtering process, many authors tried to organize the 3D cloud into multiple classes, using essentially unsupervised classification methods. The input data can be only 3D point cloud. Geometric or textural attributes are used. In Elmqvist et al. (2001), the height texture is the maximal local slope and the second derivative of the pixel and the 8-neighbouring pixels. Multiple echos allow the distinction between buildings and vegetation. Height texture is often processed over a regular interpolated grid. Suitable results can be obtained by Laplace Operator Maas (1999) or by local curvature Steinle and Vogtle (2001). Standard deviation of heights is also used. It can be processed in 3D or in 2.5D, over a titled plane or over a horizontal plane Tovari (2006).

In Charaniya et al. (2004), lidar intensity is used with geometric features to provide four classes: road, grass, building and vegetation. Other methods are based on a joint use of lidar data and optical images. Spectral and geometric attributes are then used. Spectral attributes are computed to qualify vegetation such as NDVI Steinle and Vogtle (2001), HNDVI Bretar (2007) and buildings Rottensteiner et al. (2007).

Existing methods provide adaptative solutions to specific areas or may be sensitive to negative outliers. All methods do not offer an automatic qualification of class reliability. In this study, we propose to use of the well-known K-means clustering in a hierarchical approach to filter lidar data. We propose a methodology that is based only on 3D point cloud. It is a point-based classification with regard to a fixed local neighborhood. It is especially dedicated to vegetated areas where ground points are sparse. It can deal with steep relief covered by dense vegetation, mountainous area and terrains which present microrelieves. Moreover, many algorithms depend on the neighborhood window size and try to adapt it provided a priori knowledge about the terrain topology. To overcome this problem, we propose a multi-scale framework that is processed in a coarse-to-fine way. It improves the algorithm robustness to the window size and provides reliable ground estimation.

The methodology is detailed in section 2. First, section 2.1 presents the management of the point cloud. Section 2.2 details the hierarchical filtering of the point cloud using K-means algorithm that provides a robust approximated surface. The number of cluster splits is used to automatically qualify the filtering reliability. They are jointly used with a local slope map to refine the ground points filtering (*cf.* Section 2.3). The mutliscale extension is detailed in section 2.4. Finally, quantitative and qualitative results are presented in section 4 on the ISPRS data set.

2 METHODOLOGY

2.1 Management of the point cloud geometry

Considering the DTM as a georeferenced regular gridded surface with a resolution r, the system explores the lidar point cloud following this gridded geometry. For each site s, the local 3D environment, noted $\mathcal{V}_s$, is extracted. It is designed as a cylindric neighborhood centred on s and of diameter $d_s = 2 * r$ ensures 50% overlap between 3D neighborhoods and filtering regularity.

2.2 Hierarchical K-means Filtering

We propose an unsupervised filtering based on K-means clustering of the 3D-point cloud. The clustering is processed in the feature space. Mean and standard deviation of heights are used. Generally, filtering methods depend of the window size d_s. Unlike techniques that try to adapt the window size, the idea is to use a fixed window size with a hierarchical clustering of point cloud based on series of splits of the ground cluster.

The algorithm is described in figure 1. The 3D point cloud is initialized as off-ground. For each site $s(i,j)$, the cylindric neighborhood $\mathcal{V}_s$ is extracted. First, negative outliers are filtered. If the percentage of negative points in $\mathcal{V}_s$ is over ($T_{out} = 80\%$), they are considered as outliers and labelled as Non-Determined points. The filtering starts with a coarse clustering. The centroids are initialized at equal distance on Z interval. The number of initial centroids is initialized to 1. It increases iteratively while the intra-variance cluster is higher than $1m$. The number of initial clusters can go up to three which can roughly correspond to ground, off-ground and low off-ground classes. n_{split} corresponds to a cluster map with DTM resolution. The number of splits is stored for each site s.

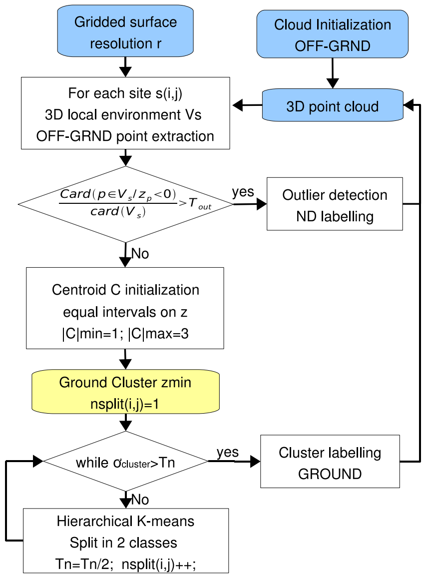


Figure 1: Hierarchical K-means flowchart.

The cluster whose average height is minimum is considered as the ground cluster. From then, it is refined iteratively. The K-means is implemented in a hierarchical way that splits the ground cluster into two classes while the cluster standard deviation $\sigma_{cluster}$ is higher than a threshold T_n. n is the number of cluster splits. The threshold is refined at each split following $T_{n+1} = T_n/2$. When the algorithm converges, the ground cluster is labeled and the propagation continues through the 3D point cloud. In case of DTM generation, the corresponding site is assigned to the average height of the ground cluster. This method provides a robust filtering of ground points. Therefore, 3D points labeled as ground are not reprocessed when moving to neighboring site.

The filtering step classes the point cloud into ground, off-ground and non-determined points. There is no need for pre-processing the data to filter the outliers. They are handled in the hierarchical filtering process and labeled as non-determined points. It also provides the corresponding cluster map. This map is used to qualify the classification reliability. The less the number of splits, the more reliable the classification. This information is used to refine the classification as detailed in the following section.

2.3 Classification refinement

As cited above, our methodology is especially dedicated to vegetated and mountainous areas. The clustering process is based on point heights and tends to minimize the intra-variance of each cluster and to maximize the height difference between clusters. A neighborhood with high variance is likely to belong either to a vegetation area or to a steep surface. The most errors occur in case of steep relief with vegetation Sithole and Vosselman (2004). Therefore, sites with a high number of cluster splits (n>2) and a high local neighborhood slope (>10°) are reprocessed to refine the classification. The estimation of the local slope is detailed in the following section. For these sites, the hierarchical K-means filtering is then processed in the fitted plane framework. The distances between clusters are unsigned to take into account both points which are above and below the estimated local plane.

Estimating the local slope Based on the assumption that the local slope changes locally in a monotonous manner, a local tangent plane is fitted, for each site s to lidar points within the cylindric neighborhood $\mathcal{V}_s$. The quality of the local plane estimation depends on the lidar point distribution within $\mathcal{V}_s$, the windows size and defines the terrain height relevancy as well as its uncertainty. We estimate a plane $n_x x + n_y y + n_z z + d = 0$ with $(n_x, n_y, n_z) \in [-1, 1]$ and $d \in \mathbb{R}$. A robust M-estimator has been used with a L_p-norm, p=1.2 Xu and Zhang (1996). This algorithm is implemented as an iterative re-weighted least square system. At each DTM site, the steepness (the elevation angle of the surface normal) is processed, leading to a slope map. Figure 3(b) has been processed on the sample 52 of ISPRS data set. One can observe the discontinuity on the right of the image and the sharp ridges. The contribution of the local slope is discussed in Section 4.1.

2.4 Coarse to Fine implementation

The evaluation of the algorithm robustness (Section 4.1) showed that results are very sensitive to the neighboring window size and to the DTM resolution. It gives good results provided a priori knowledge. Tuning the parameters is difficult. To overcome this problem, we propose a multiscale approach for extracting ground points. The idea is to start at coarse resolution with a high window size to ensure to have some ground points. This may lead to the surface overfitting. The result is refined later at fine resolution with a small window size. The clustering method is still hierarchical. The difference is that the fine ground cluster tends to minimize the mean and the standard deviation of differences between ground points heights and the estimated elevation (at coarse resolution).

Evaluations (Section 4.3) proof that the coarse-to-fine method ensures a high reliability for ground points, that is independent of the neighborhood size. Moreover, since the finer stage is based on the coarse DTM, the methodology saves computation time.

3 THE DATA SET

The algorithm has been tested on various data sets, especially on vegetated areas with different topography. The algorithm is first analyzed on one data set and then quantitative and qualitative evaluations are presented over several others. The datasets are those made available for the ISPRS WG3/III test Sithole and Vosselman (2004). These data are considered as a reference for evaluating filtering algorithms. A ground truth of ground/off-ground classification is provided. It was performed manually in a controlled manner.

In this study, we are interested on vegetated, mountainous and steep relieves. Consequently, we selected the FSite5 data set with 2 m resolution. Provided the ground truth, the incorrect classification is qualified by two measures: Type I error (classify ground points as non-ground) and Type II errors (classify non-ground points as ground). Unlike the ISPRS study, where some lidar points are unused, all the lidar points are taken into account for evaluations.

4 RESULTS AND DISCUSSION

Table 1 summarizes the characteristics of the proposed method.

Description	I/O Format	# of operator settings
Hierarchical iterative K-means	Point List Grid	3 DTM resolution neighborhood size T_0 variance intra-cluster T_n

Table 1: Characteristics of the proposed method.

Compared to other methods, the algorithm depends on few parameters. The robustness of the algorithm to these parameters is evaluated in section 4.1. Results and evaluations are first detailed on sample 52 dataset. The contribution of local slope is also demonstrated. The results on previously described datasets will be compared to other filtering algorithms Sithole and Vosselman (2004). These evaluations will entail a coarse-to-fine implementation that makes the algorithm more robust and less sensible to the window size. Results will be also presented on the same areas.

4.1 Hierarchical K-means filtering

Sample 52 deals with quarry and low vegetation on river bank with gaps. The 3D point cloud is shown in figure 2. Figure 3 shows the used landscape predictors to locally refine the classification. The algorithm was processed with a DTM resolution of 2 m and a neighborhood size of 30 m. The cluster split map is shown in figure 3(a). The less the number of splits, the more reliable is the ground cluster. One can observe that the number of clusters increases in the steep surface. Figure 3(b) shows the slope degree map. The combination of both maps leads to the sites that have to be reprocessed to refine the classification (figure 3(c)).

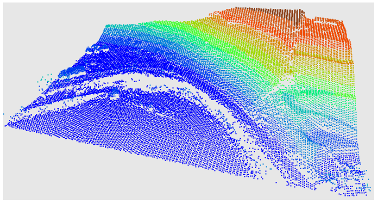
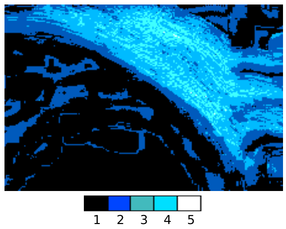
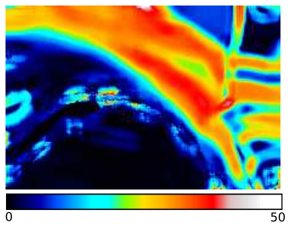


Figure 2: Sample 52 - 3D point cloud.



(a) Cluster map.



(b) Slope degree map.

(c) Locally retreated points.

Figure 3: Sample 52 - landscape predictors.

Contribution of local slope Table 2 compares the type I and type II errors after processing the confusion matrix.

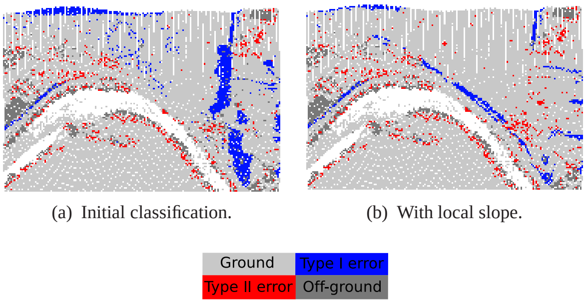
Method	Type I	Type II	Total
Initial classification	7.36%	3.87%	11.23%
Classification refinement	3.10%	4.57%	7.67%

Table 2: Contribution of cluster and slope maps,DTM resolution=2 m, neighborhood size= 30 m.

The refinement of classification decreases the total error. The type I error is improved which means that less ground points are classified as off-ground thanks to the estimation of the surface slope. Figure 4 shows the confusion images with the initial classification and the refined one using the slope map. The result is improved on the right crest where the points are classified as ground in the surface plane framework.

Algorithm robustness to parameters In this section, quantitative evaluations measure the algorithm robustness to its parameters. Type I, Type II and the total errors are processed.

Figure 5 illustrates the impact of the neighborhood size on the evaluation with a fixed DTM resolution of 2 m. Best results are



(a) Initial classification. (b) With local slope.

Figure 4: Sample 52 - Impact of the local slope: comparison of confusion images.

obtained with a neighborhood size $d_s = 5\,m$. However, when d_s increases, the type II errors are almost constant but type I errors increase. This means that more ground points are classified as non-ground. In fact, with a large d_s, the estimated plane may be erroneous in case of a relief changes and the terrain can be overfitted. Figure 6 shows the evolution of errors with the DTM resolution. The total error increases at coarse resolution of the DTM. However, the more r increases, the more type II error decreases. This property will be used in the coarse-to-fine implementation 2.4.

These evaluations show that the algorithm is sensitive to parameter tuning. For such a terrain, with a fixed neighborhood size, we still need an a-priori knowledge to choose the window size.

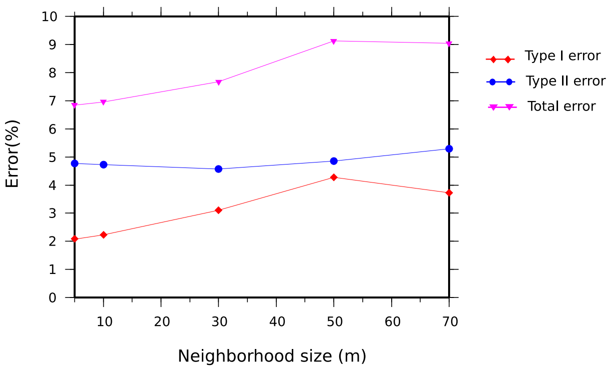


Figure 5: Evaluation of the neighborhood size impact, DTM resolution=2 m.

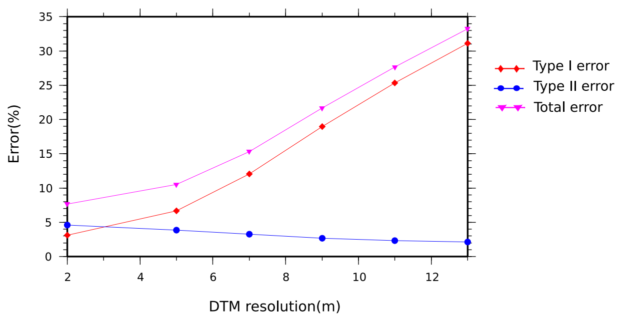


Figure 6: Evaluation of the DTM resolution impact, neighborhood size=30 m.

4.2 Comparison with filtering algorithms

In this section, table 3 shows quantitative comparison of the proposed method with other filtering algorithms described in Sithole and Vosselman (2004). Three datasets of Fsite5 are used. The sample 52 which was used previously. The sample 51 is characterized by vegetation on slope. Finally the sample 53 raises the discontinuity preservation problem. For this comparison, we used a DTM resolution of 2 m and a neighborhood size of 10 m.

Sample	Method	Type I	Type II	Total
51 (17845 pts)	Elmqvist	49.34%	1.60%	50.94%
	Sohn	10.33%	5.68%	16.01%
	Axelsson	0.13%	12.00%	12.13%
	Pfeifer	4.21%	1.93%	6.14%
	Brovelli	28.23%	3.64%	31.87%
	Roggero	1.90%	6.96%	8.86%
	Wack	14.03%	2.23%	16.26%
	Sithole	7.03%	6.99%	14.02%
	Proposed meth	0.04%	7.31%	7.35%
52 (22474 pts)	Elmqvist	85.05%	1.27%	86.32%
	Sohn	12.34%	9.48%	21.82%
	Axelsson	1.78%	14.21%	15.99%
	Pfeifer	21.27%	5.68%	26.95%
	Brovelli	50.43%	3.84%	54.27%
	Roggero	9.80%	9.66%	19.46%
	Wack	26.49%	1.04%	27.53%
	Sithole	30.41%	3.57%	33.98%
	Proposed meth	2.23%	4.73%	6.96%
53 (34378 pts)	Elmqvist	92.45%	0.18%	92.63%
	Sohn	20.48%	13.24%	33.72%
	Axelsson	8.58%	16.76%	25.34%
	Pfeifer	12.53%	14.23%	26.76%
	Brovelli	54.93%	1.62%	56.55%
	Roggero	17.81%	4.74%	22.55%
	Wack	28.33%	1.02%	29.35%
	Sithole	38.41%	4.81%	43.22%
	Proposed meth	2.15%	2.16%	4.31%

Table 3: ISPRS data sets. Quantitative evaluations of errors with comparison to the ground truth.

For each sample, we highlighted the best results among filtering algorithms and the proposed method. In all cases the proposed method decreased the total errors. Moreover, it provides smaller type I errors, which means that few ground points are classified as off-ground. However, it might present heavy type II errors. This is due to the use of a relatively small neighborhood size. some off-ground objects may be classified as ground.

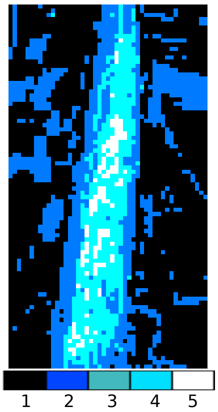
Figure 7 shows confusion images on samples 51 and 53. One can observe that heavy type II errors occur in sample 51 on rooftoops since their size is smaller than the used neighborhood size.

4.3 Coarse to Fine implementation

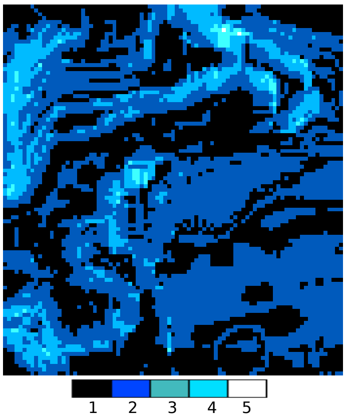
For terrain modeling, the ground estimation should be robust and type II error should be minimized. Based on parameter evaluation (section 4.1), we propose a coarse-to-fine implementation to decrease type II errors. A coarse DTM resolution ensures a reliable ground estimation, the finer resolution should decrease the type I error. Figure 8 shows the evolution of confusion images from the coarse resolution to the finer one. At coarse resolution, $r = 15\,m$ and neighborhood size $d_s = 30\,m$. At fine resolution $r = 2\,m$ and $d_s = 5\,m$. Figure 8(a) shows, at coarse resolution, heavy type I errors due to the large DTM resolution. Figure 8(b) shows the results at fine resolution. The total errors are clearly decreased. Figure 8(d) shows the spatial differences between the coarse DTM height and the fine ground cluster mean height. Negative differences are along the steep surface which was overfitted at the coarse stage. Besides, high positive differences occur on the right of the image, in presence of discontinuity.

Table 4 compares the errors between the fixed neighborhood size and the coarse-to-fine implementations.

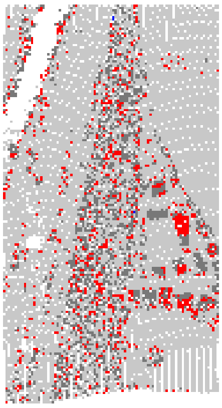
Type II errors decreases with the coarse-to-fine implementation. The ground estimation is more reliable for a terrain modeling application. The coarse-to-fine implementation makes the algorithm robust the neighborhood size and the DTM resolution. It combines the advantages at each resolution. It allows to preserve



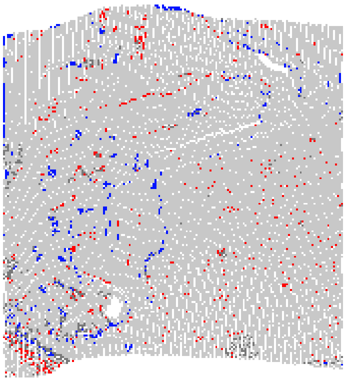
(a) Sample 51 - cluster map



(b) Sample 53 - cluster map



(c) Sample 51



(d) Sample 53

Figure 7: Fixed neighborhood size 10 m. Confusion images on Fsite5 dataset.

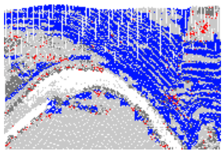
the discontinuities and to deal with steep relieves.

5 CONCLUSION AND PERSPECTIVES

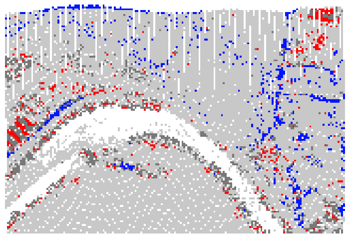
We proposed in this study, the use of K-means clustering in a hierarchical way to filter lidar data. The methodology provides good results with comparison to other filtering methods. Moreover, this algorithm provides an automatic classification quality thanks to the cluster map which is useful in case of human operator correction. The proposed classification is based on local neighborhood and can lead to misclassification in the presence of complex objects. Landscape predictors are clearly needed to tune the parameters. We used the cluster map and a slope map to refine locally the classification. However, the parameter evaluations showed that the algorithm is sensitive to the window size

Sample	Method	Type I	Type II	Total
Sample 51	Coarse fixed d_s	12.32%	4.79%	17.11%
	Fine fixed d_s	0.039%	7.31%	7.35%
	Coarse-to-fine	0.65%	6.33%	6.98%
Sample 52	Coarse fixed d_s	36.99%	1.75%	38.74%
	Fine fixed d_s	2.23%	4.73%	6.96%
	Coarse-to-fine	4.37%	2.99%	7.36%
Sample 53	Coarse fixed d_s	34.72%	0.91%	35.63%
	Fine fixed d_s	2.15%	2.16%	4.31%
	Coarse-to-fine	5.93%	1.27%	7.20%

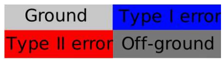
Table 4: Contribution of cluster and slope maps,DTM resolution=2 m, neighborhood size= 30 m.

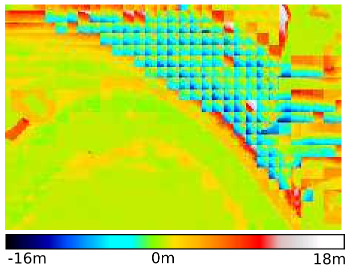


(a) Confusion image at coarse DTM resolution (15 m)



(b) Confusion image at fine DTM resolution (2 m)





(d) Altitude difference (coarse DTM - fine ground cluster

Figure 8: Sample 52 - Coarse-to-fine Approach

and the DTM resolution. To overcome this problem, a coarse-to-fine implementation is proposed. The classification at a coarse level helps dealing with discontinuities, gaps and complex objects. The finer step takes into account local features as slope. The ground estimation is more reliable with the mutiscale approach.

The advantage of K-means clustering is that it can be easily adapted to available data by modifying feature attributes. Clustering may be then processed in a multidimensional feature space. In the proposed algorithm, only geometric attributes are used to separate ground from off-ground points. Spectral attributes could be used for fine classification purposes of off-ground objects. As a perspective, the cluster split map could be also used for a multiple resolution process of the lidar point cloud. In case of one cluster (ground), the lidar data can be under-sampled to reduce computing time.

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