

3D CLASSIFICATION OF POWER-LINE SCENE FROM AIRBORNE LASER SCANNING DATA USING RANDOM FORESTS

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Commission III, WG 2

KEY WORDS: LIDAR, classification, power-line scene, random forests, ensemble classifier, Weka

ABSTRACT:

Since the introduction of Airborne Laser Scanning (ALS) known as an alternative aerial-based data acquisition tool, the requirement of the 3D model reconstruction in both urban and power-line scenes has dramatically increased. Especially, electric utilities including power-line and tower are crucial infrastructures that require considerable resources to be monitored and managed effectively. For the establishment of the power-line scene inventory, its geospatial information such as positions and attributes of power-line networks should be accurately recorded. This paper presents a 3D classification method to classify power-line scene where a few structures including trees, transmission lines and pylons would be vertically overlapped. The research proposes two different scales of feature extractions from a volumetric space and its embedded points for taking advantages of full 3D analysis against conventional 2D pixel-based analysis. With targeted object instances including ground, vegetation, power-line, pylon and building, 21 features to characterize each class are extracted from different segment scale. The Random Forest is investigated as an ensemble decision classifier to classify power-line scenes with extracted features. An ultimate goal of the research is to apply a knowledge-based classifier trained with small training sample to large-scale unlabelled power-line corridors. In order to achieve this goal, this paper conducts a sensitivity analysis in terms of feature extraction scale, feature importance and class distribution over test datasets with or without the separation from training data. Experiments suggest that an optimized classification performance of 96% success rate by Random Forest can be achieved with point-based feature extraction and data sets with relatively equal distribution of the training data.

1. INTRODUCTION

3D object reconstruction in urban, suburban, and power-line scenes has become an interesting issue independently on specific data: aerial images, ALS (Airborne Laser Scanning), and TLS (Terrestrial Laser Scanning). Currently, the frequency of the use of ALS data has dramatically increased compared to other sensory data due to its advantageous ability of direct 3D measurement with high density, accuracy and foliage penetration. Recently, a summary of advanced photogrammetry and remote sensing technologies using ALS for scientific and engineering applications was addressed in Shan and Toth (2008) and Vosselman and Mass (2010). However, most of ALS-based researches for 3D object reconstruction mainly focused on few numbers of urban (i.e., building, terrain and road) and natural (trees, canopy and forest) features. Not many research works has been reported in the automation of corridor objects such as power-line networks. Power-line network is considered as one of the most important infrastructures in North America which requires reliable monitoring of its safety. Recently, Jwa et al. (2009) introduced an automatic algorithm to reconstruct 3D transmission models from ALS point of clouds using non-linear least square regression method. Most of the proposed methods for reconstructing 3D urban and natural objects require a reliable classification of ALS data based which 3D modelling algorithm can be applied. The accuracy of 3D modelling is primarily subjective to the classification errors. In addition to the importance of achieving high quality of classification results, its cost-effectiveness should be concerned, in particular as the algorithm deals with massive scale of modelling coverage and spatial-temporal applications. This is the case for power-line risk management using ALS data. This research addresses the

problem of knowledge-based classification when it is trained with relatively small training samples, but tends to be applied to large-scale unlabelled data for power-line scene classification.

2. RELATED RESEARCH

Classification approaches can be divided into two categories: binary classification and multi-class classification. The binary classifier aims to classify given scene into pre-dominant two features which is often used for solving the fore-to-background problem. For instance, Sohn and Dowman (2002) separated ground features from non-ground ones which stand above the ground by developing RTF (Recursive Terrain Filter). This terrain filter progressively finds terrain points through evaluating candidate points identified from the iterative TIN defragmentation in downward step and upward step. Baillard and Maître (1999) represented an objective function of the binary classification to separate ground features from above-ground ones based on the MRF (Markov Random Field) using 3D information. Rutzinger et al. (2008) developed an object-based point cloud analysis for classifying ALS data into vegetation and non-vegetation features using the ALS Full-waveform-driven information. Multi-class classification aims to classify ALS data into multiple object classes rather than two instances at one simultaneous process or by a hierarchical multi-segmentation. In this category, Axelsson (1999) proposed an algorithm which enable to segment ALS data per scan line into ground, building, or power-line by applying the MDL (Minimum Description Length). Not only using ALS data, Lalonde et al. (2006) classified the objects on the terrain into three classes: rough surface objects such as grass and tree

canopy, linear-like features including wires and tree branches, and smooth surface such as ground surface, rocks or large trunks using range data collected by laser mounted mobile mapping system. They demonstrated three object classes can be separable by Bayesian classifier which investigates geometric salient features captured from laser point distribution in a local neighbourhood. The limitation of deterministic classification methods mentioned above is the use of user-specified thresholds.

A new approach for classification of ALS data is to use machine learning techniques: Support Vector Machine (SVMs), decision tree, boosting, neural networks and so on. The Random forests (Breiman, 2001) is recently emerged as a state-of-the-art machine learning technique which considers ensembles of decision trees, rather than single tree generated by a base classifier. The advantage of Random Forest (RF) does not rely on use-specific thresholds for its decision. Furthermore, there nearly is no limitation with the number of feature variables required for decision node splitting. Compared with other classifiers, the accuracy of the RF is as good as Adaboost which is well known classifier with high success in machine learning. Additionally, the RF automatically sorts feature variables on the basis of variable importance for best splitting at each node. Narayanan et al. (2009) apply ensemble classifiers including the RF for generating under-water habitat maps using the Optech's SHOALS system. They choose the best classifier through a quantitative comparative analysis of the ensemble classifiers and apply the selected classifier for benthic habitat classification. Carlberg et al. (2009) labelled the ALS data into a few of object classes including water, ground, roof, tree, and others. The method was developed based on a cascade of binary classifiers specifically trained for the individual class. The unlabelled lasers points were progressively classified by a set of the proposed binary classifiers using the RF. Chehata et al. (2009) produced a RF classifier using several important features among designed 17 features for the purpose of urban scene classification. The ensemble classification was accomplished using 2D rasterized data which might lead to an ambiguity between building and ground.

In this paper we investigate the potential of the RF classification for power-line modelling application using the ALS point of clouds. An ultimate goal of the research is to apply a knowledge-based classifier trained with small training sample to large-scale unlabelled power-line corridors. In order to achieve this goal, this paper conducts a sensitivity analysis in terms of feature extraction scale, feature importance and feature distribution over test datasets with or without the separation from training data. In addition, the presented research focuses on the classification advantages gained by a 3D profile analysis which extract classification features computed from vertical segments. A vertical distribution of classified features and their topological and semantic relations can be used as additional reasoning cues for rectifying the RF classification results populated in a point-wise processing manner. As address in Chehata et al. (2009), an uncertainties where several objects are overlapped at one place (e.g., trees standing nearby buildings) can be resolved if a 3D analysis for its vertical superposition is investigated. This paper is outlined as follows: the next section describes a pre-processing procedure to detect terrain features for attributing the above-ground points in height and multiple-feature extraction for the RF decision. In section 4, we describe the Random Forest as a selected ensemble classifier which is trained using features computed from 3D volumes. Finally, we present experimental results and draw conclusions with respect to the sensitivity analysis of the RF in terms of feature extraction scale, feature importance and feature distribution

over test datasets with or without the separation from training data.

3. PREPROCESSING AND FEATURE EXTRACTION

3.1 Terrain filtering

The most of power-line networks are built in open spaces where ground feature are predominant compared to the occupancy of the other features. Under these circumstances, the ground points are typically recognized as a dominant feature. If any object (i.e., terrain feature for power-line scene) feature over-occupies a given scene, its biased feature distribution would cause errors in a fair training of the machine learning algorithms. Thus, for improving decision tree training, the contribution of the terrain feature should be excluded in advance. The efficiency of currently existing terrain filtering algorithms which have been developed over the past years has been already validated. In this study, we use a RTF (Recursive Terrain Filter) developed by Sohn and Dowman (2002) to identify the terrain feature. However, the classified terrain is taken into consideration while computing feature variables.

3.2 Segmentation

LIDAR is usually pre-processed in three ways depending on the segment scale for the purpose of reducing the complexity and simplifying a scene: point-based, 2D grid-based, and voxel-based. The first method has an advantage of that each point possesses original values on features, but it has a drawback to the processing time due to handling individual points. A spherical volume is traditionally used to find neighbours of a certain point. The second might make a result much more quickly, but the height of each point could be neglected due to the dimensional reduction and the height interpolation. The last way has the benefit of maintaining three dimensional information of point and shortening its throughput at the same time.

In the both voxel-based and sphere-based segmentation, the most important factor is the segment size. It is generally decided by the space which certain patterns can be extracted from the member points in. When it is too big, points corresponding to two or more different classes could be combined in a huge segment. On the other hand, it could be difficult to identify the part of a structure due to few points of a voxel if it is too small. In this study it is a minimum size to recognize that the member points of a segment are a part of a natural or a man-made structure, and it is determined by a sensitivity analysis on extensive segment sizes as performed in section 5.5. The optimal segment size dependent on the unit of 3D point cloud is chosen to 3 meter or 10 feet. In spite of the optimal size, however, the mixture of points belonging to two or more structures surely exists at the place where two structures are linked. For instance, all vegetations are always grown on the ground and vegetations under the clearance violation reach power-lines. The classification errors would frequently occur among these segments. The 3m of voxel and 1.5m radius of sphere are respectively used for voxel- and point-based feature extraction.

3.3 Feature variables

The feature variables are computed from the geometry of member points within the volumetric space segmented by voxel (voxel-based) and sphere (point-based). For point-based feature

extraction, features of a certain point are computed by using its neighbours within a spherical space with a fixed radius from the point. Thus, the following 21 features are extracted per each voxel and point. Figure 1 includes the colorized map of the ground truth and several important features derived by the point-based feature extraction approach.

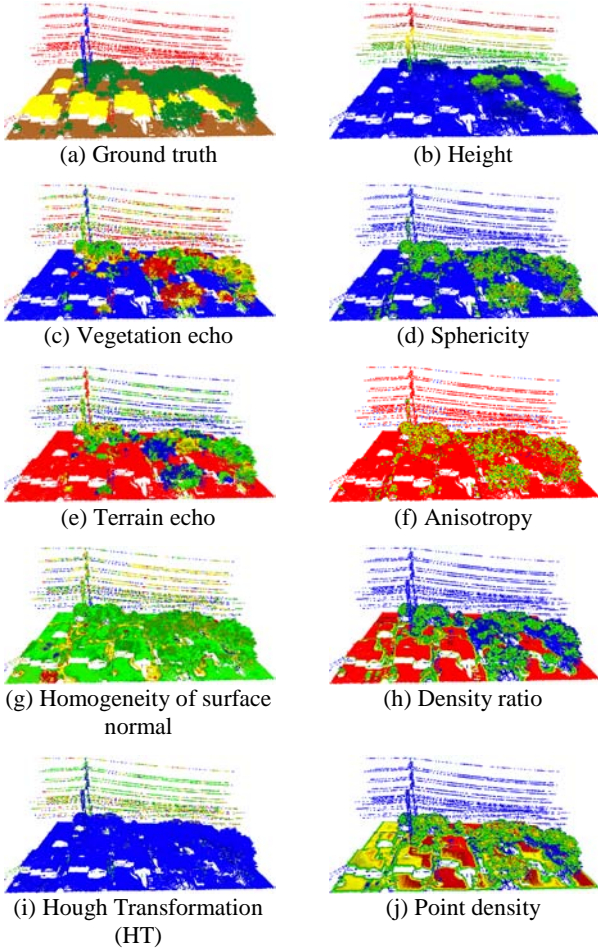


Figure 1. Ground truth and 9 important features (blue: low and red: high)

3.3.1 Height from ground level

A digital terrain model (DTM) is formed by the recursive TIN fragmentation in every downward and upward stage (Sohn and Dowman, 2002). The height is the vertical distance from a certain point to the previously formed terrain surface in both approaches. If the terrain is one of the target classes whose classification is necessary, this would be the most important feature.

3.3.2 Hough transformation (HT)

The HT, which is a general method to extract linear objects such as roads from images, needs to be enhanced prior to being applied to the two dimensional points that are projected onto the base plane of each segment. This is because the projected power line points cannot be placed on an ideal straight line due to the system errors of ALS (the horizontal error with a laser scanner, the vibration of airplane, and GPS/IMU error) and environmental effects (ice and wind load). Additionally, multiple wires could exist within a segment. Therefore, for the HT value we consider a global maximum and several local maxima existing in the range near the θ corresponding to the global maximum bin in an accumulating matrix of the HT

domain. In here it is supposed that the multiple wires are parallel each other. When the perpendicular angle to the orientation direction of the line with the global maximum is θ_{gmax} , the range of $\theta_{gmax}-1$ to $\theta_{gmax}+1$ is taken into account to find local maxima bins. The θ size of a bin is 2 degrees, so the range for local maxima search is $\theta_{gmax} \pm 2^\circ$. Conclusively, the HT value considering the votes of a global maximum and local maxima is defined by:

$$HT = \frac{V_{gmax} + \sum_{i=2}^{N_{max}} V_{i^{th}max}}{N_{pt} \times N_{max}} \quad (1)$$

where, V_{gmax} = the vote of a global maximum bin
 $V_{i^{th}max}$ = the vote of the i^{th} local maximum bin existing between $\theta_{gmax} \pm 1$
 N_{max} = the number of maxima bins
 N_{pt} = the number of points within a segment

3.3.3 Eigenvalue-based

The eigenvalues are computed from the covariance matrix between x, y, and z of 3D points. Supposed that the extracted eigenvalues are λ_1 , λ_2 , and λ_3 ($\lambda_1 > \lambda_2 > \lambda_3$), three variables might have different values according to following three cases: $\lambda_1 \approx \lambda_2 \approx \lambda_3$ for scattering points, $\lambda_1, \lambda_2 \gg \lambda_3$ for points on surfaces, and $\lambda_1 \gg \lambda_2, \lambda_3$ for linear structures. On the basis of this principle, the following features on eigenvalues are defined (Chehata et al., 2009):

Anisotropy, which is opposed to isotropy, means the homogeneity of point distribution in three arbitrary perpendicular axes. This feature is useful to separate anisotropic structures except for vegetation.

$$Anisotropy = \frac{\lambda_1 - \lambda_3}{\lambda_1} \quad (2)$$

Linearity: This helps to detect linear structures similarly to the HT. However, the linearity on eigenvalues also shows high values at building edges as well as power-line.

$$Linearity = \frac{\lambda_1 - \lambda_2}{\lambda_1} \quad (3)$$

Planarity: Planar structures such as ground and building roofs could be extracted by this feature.

$$Planarity = \frac{\lambda_2 - \lambda_3}{\lambda_1} \quad (4)$$

Sphericity: This indicates the magnitude of equally distributing in all three directions for points. Vegetation could be strong.

$$Sphericity = \frac{\lambda_3}{\lambda_1} \quad (5)$$

3.3.4 Surface-based

The plane-based features are measured by generating an estimated plane or TIN models from member points of a given segment. These are associated with surface slope, surface roughness and homogeneity of surface normal.

Plane slope: This is the angle difference between normal vector of an estimated plane and the z direction. The neighbouring points are regressed by a plane. Building roofs and ground mostly have weak values compared that vegetation has random values.

Homogeneity of surface normal: TIN generation is first necessity to create a surface model. This feature is the variance between the normal vectors of TINs. Vegetation has very high value in the variable.

Surface roughness: This feature is the root mean square of the orthogonal distance from points to an estimated plane. Vegetation would stand out since its point dispersion.

Distance to surface: This is closely similar to the *surface roughness*, but is the vertical distance between individual point and an estimated plane.

3.3.5 Convex hull-based

XY projection area: For this feature, the member points are projected on XY-plane, and then the convex hull of the 2 dimensional points is run to derive their boundary. *XY projection area* is area of the region formed by the 2D convex hull. Ground and building roof could have high value of the area. On the contrary, power-line has almost zero value.

Bounding volume: Through computing the 3D convex hull of member points, the bounding volume of the polyhedron shaped by the points can be estimated. Unlike the *XY projection area*, *bounding volume* might be strong in only case of vegetation.

3.3.6 Echo-based

Echo-based features are determined by combining the number of points corresponding to single (N_s), first (N_f), intermediate (N_i), and last return (N_l). N_{pt} is the number of all member points. In here, the single return indicates a unique reflection without multiple returns, and the first return means the first reflection among multiple returns.

Terrain echo: Although terrain points are not importantly dealt with in this study, this feature would be helpful to roughly classify raw data including terrain. Terrain is mainly recorded as single return or last return. Therefore, the two returns are considered for terrain echo.

$$TerrainEcho = \frac{N_s + N_l}{N_{pt}} \quad (6)$$

Vegetation echo: The efficiency of this feature has been already validated by Rutzinger et al. (2008) for urban vegetation classification. Generally, vegetation has a considerable amount of intermediate returns due to multi-return from its leaves. In addition, the first return would be found on crown surface of vegetation. Consequently, vegetation mostly has the intermediate return and the first return in LIDAR.

$$VegetationEcho = \frac{N_f + N_i}{N_{pt}} \quad (7)$$

Power-line echo: Power-line structure should be constructed on an open place which is not surrounded with any natural or artificial obstacles dangerous enough to break down it or where the obstacles have been removed by human. Accordingly, a laser pulse hitting a power-line has mainly a first return reflected from the power-line. Furthermore, the foot print size of the laser which approaches a power-line is bigger than the diameter of the power-line. That is, there would be another return from typically ground. Therefore, power-line is generally first return among the multiple returns, not single return.

$$PowerlineEcho = \frac{N_f}{N_{pt}} \quad (8)$$

Building echo: A laser cannot surely penetrate building roofs made of the concrete materials. In other words, there is no more return excluding a reflection from roofed top. Building echo considering only single return is defined as follow:

$$BuildingEcho = \frac{N_s}{N_{pt}} \quad (9)$$

3.3.7 Density-based

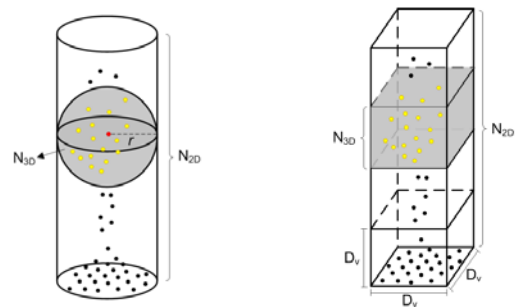
Point density: is the number of points within a given segment divided by its volume. Generally, these for ground and building roof are the largest and vegetation is stronger than power-line in the value.

Density ratio: This feature was also invented by Rutzinger et al. (2008) to differentiate vegetation. According to his method as shown in figure 2(a), density ratio of a certain LIDAR point means a ratio between point densities of a projected circle from a cylinder of radius r and a sphere of radius r (Eq. 10). This method is applied for point-based approach. However, for voxel-based approach, this is rearranged by considering a cube and a rectangle instead of a sphere and a circle as the figure 2(b). It is defined as Eq. 11.

$$DR_{3D/2D} = \frac{N_{3D}}{N_{2D}} \times \frac{3}{4r} \quad (10)$$

$$DR_{3D/2D} = \frac{N_{3D}}{N_{2D}} \times \frac{1}{D_v} \quad (11)$$

where, N_{3D} and N_{2D} are the number of points within a target segment (sphere or voxel) and the projected shape (circle or rectangle) respectively. The r and D_v indicate radius of a sphere and the voxel size. The overhead and separated power-lines have low values because of plenty of ground points under it. It is very high in case of objects with dense points around such as ground and building. Vegetation would be between power-line and ground.



(a) Point-based computation (b) Voxel-based computation
Figure 2. 3D/2D density ratio

3.3.8 Vertical Profile

Vertical structures such as trees, streetlights and power-line towers show the vertical continuity of on-segment, in here on-segment means the segment occupied with one or more points. In contrast, floating structures like power-line have a few of vacant segments called off-segment. For extraction of these features, a vertical profile (rectangular column for voxel-based or cylinder for point-based) is sliced by several bins of 75cm height (a quarter of segment size).

On-segment: is the number of on-segments along to a vertical profile.

Continuous on-segment: This feature value corresponds to the maximum count of on-segments stacked continuously. It is

investigated for detecting a vertically formed structure like electric pylon. Pylon and high vegetation have high values.

Continuous off-segment: This is the opposite of *continuous on-segment*. Overhead power-line would have high count because of empty space between ground and power-line.

4. 3D CLASSIFICATION WITH RANDOM FORESTS

Every voxel and every point respectively posses the 21 features derived through the voxel- and point-based feature extraction when there are more than a given number of member points. For voxel-based feature extraction, the all feature values of each voxel are assigned to its member points. After that, the Random Forests (RF) is applied to points which a pair of the 21 features have been assigned to by the two feature extraction approaches in order to tag them into one of following classes: ground, building, vegetation, wire, and pylon. The RF is an ensemble classifier which is able to generate considerable number of decision trees learned by a partial or entire training data set and then derive an optimal tree which minimizes the generalization error among previously generated trees. For the RF we used a customized Weka 3.5.1 which includes some implemented functions - the evaluation of variable importance, interactions and proximities between individual decision trees, and so on. The variable importance of the customized Weka is perfectly same as Breiman’s algorithm (Breiman, 2001). For training, the RF fixed $M = 4$ and $T = 60$, which mean the randomly selected feature number at every node split and the number of populated trees, in order to lead a learned classifier to be independent on a training sample.

5. EXPERIMENTAL RESULT

5.1 Training set (TR) and test set (TE)

The test data set was acquired along to east and west of Folsom, California, USA in August for the purpose of power-line management in order for violation clearance against vegetation. The coverage of the data is approximately $6870(EW) \times 1263(SN)$ m^2 and it was collected using Riegl Q560 with $30/m^2$ of the point density on average. Two subsets are taken from regions 2.5km away in the original data set: a training set (TR) and a test set (TE). The both data contain not only terrain, vegetation, power-line, power-line tower, and building which are interesting classes in this study, but also are manually or semi-automatically classified by a worker with a plenty of experience. We regard the manual classification output as a ground truth. The scene similarity between TR and TE considerably affects the classification result of TE. This is because the classifier learned by TR depends on the extracted features and they computed from TE would be similar to TR’s. Table 1 summarizes the data characteristics between TR and TE. The likeness would be expected to lead a good classification result of TE, but our experiments more focus on the comparison of two approaches with respect to the feature extraction depending on a segment scale (point or voxel) and sensitivity analysis regarding the class uniformity. Thus, the main experiments are categorized into two tests: voxel-wise versus point-wise feature extraction, and classification with and without ground points. Another experiment is to determine the best segment size through a sensitivity analysis.

Setting	TR	TE
Points	194,289	484,092

Point density	38.75/m ²	32.29/m ²
Surface slope	0.5°	0.05°
Bldg. roof type	Gable	Gable
Power-line voltage	115kV	115kV
Pylon type #1	Lattice	Lattice
Pylon type #2	3-level	3-level
Tree proximity	close to building and pylon	close to building

Table 1. Data similarity of TR and TE

5.2 Voxel-wise vs. Point-wise Feature Extraction

General approaches for feature extraction which dealt with 3D point cloud average feature values with member points of a segment or interpolate them with neighbouring segments. That method is called segment-wise feature extraction. In the contrary, point-wise method handles the original values of points without any interpolation and simplification. We derived 21 features for each voxel and each point based on two different volumetric approaches with respect to segment scale: voxel-wise and point-wise. After that, the feature values extracted by voxel-based method are assigned to member points of each voxel. That is, each point has two values corresponding to a feature variable. The RF was applied for comparative analysis of the performance of the two extraction approaches. The TR was split into 1/10 for training and 9/10 for validating (leave-one-out), which is similar to 10-fold cross validation typically used in machine learning.

Class	Grnd	Veget	Wire	Pylon	Bldg	Accuracy(%)
Grnd	79,215	49	0	0	14	99.92
Veget	82	63,447	96	3	429	99.05
Wire	2	95	5,803	78	22	96.72
Pylon	2	55	105	912	4	84.60
Bldg	23	404	30	0	23,848	98.12

Table 2. Confusion matrix for TR using voxel-wise method (M=4 and T=60)

Class	Grnd	Veget	Wire	Pylon	Bldg	Accuracy(%)
Grnd	79,206	57	5	0	10	99.91
Veget	111	63,449	26	4	467	99.05
Wire	3	93	5,840	62	2	97.33
Pylon	2	43	38	995	0	92.30
Bldg	26	679	46	0	23,554	96.91

Table 3. Confusion matrix for TR using point-wise method (M=4 and T=60)

The confusion matrices corresponding to the validation result of the trained classifiers with respect to the two feature extraction approaches are given in table 2 and table 3. The point-wise method is more uniform than the voxel-wise method in the classification accuracy of each class. This happened because the spherical volume for neighbourhoods search is more valid than arbitrary segmented voxel in terms of a certain point. Nevertheless, the voxel-based approach led for a reasonable success rate. In addition to its good accuracy, it could be applied for quick classification of a large-scale corridor data thanks to its short computing time in feature extraction. However, we applied the point-wise approach for all next experiments. In both table 2 and table 3 the learned classifiers have a considerable uncertainty between vegetation and building compared to the others. It is because some of trees stand very closely to building and some of the trees’ branches were extended right on building roof top in the TR.

5.3 Classification with and without ground points

The limitation of the classification algorithm of the machine learning including the RF is that a trained classifier strongly depends on the class with the highest frequency. That is, the classifier is not suitable for detecting minor classes. The ground is one of the dominant classes in power-line scene as well as sub-urban area. The RTF terrain filter described in section 3.1 can remove ground points out of untagged LIDAR data. Once removing them, the frequency of the remaining classes might be almost equal. Figure 4 represents the variation of variable importance considering and not considering ground and 9 features which seem to be critical without ground are only shown. According to the figure 4, the *Height*, contributing feature to terrain detection, appeared to be less important without ground, but it is still the most critical feature for the other classes. While, the importance of *Anisotropy*, *Density Ratio*, and *HT* increased. This means the trained classifier was changed to be sensitive to the others. Another way to resolve this limitation is to take out a training set in which all classes are uniformly distributed (Lodha, 2007). For this test the RF was run based on feature derived by point-wise approach using both ground removed TR and TE.

When comparing to TEIG and TEEG in figure 5, the classification accuracy of vegetation, pylon, and building was somewhat improved since a fair classifier which is able to care minor classes. Additionally, the importance of features relevant to them was increased. However, power-line is nearly same as previous one in spite of increasing importance of *HT*. Perhaps there would be certain features substituting for *HT* in the sample with ground.

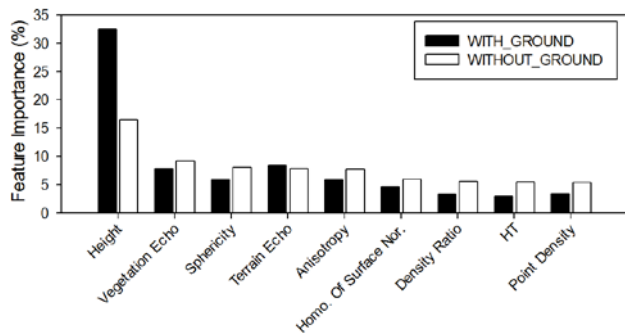


Figure 4. Variation of variable importance (with TR)

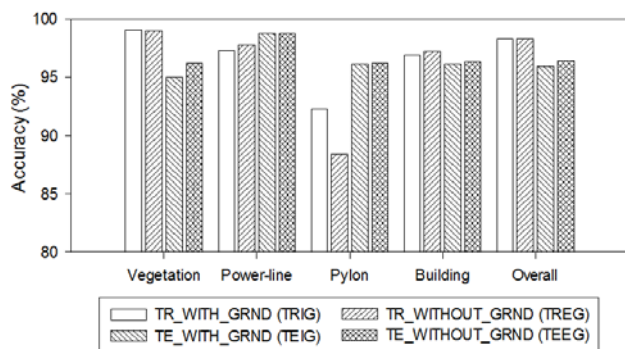


Figure 5. Classification result of TR and TE with and without ground points

5.4 Important feature selection

We selected 9 important features for classifying samples without ground in section 5.3. The TE without ground was applied for comparing performance when the RF uses 9 features

and entire features (Table 4). Most were classified similarly to the result of the method using entire features excluding electric pylon. There were not any features enabling to characterize pylon among the 9 features. Figure 6 depicts the classification map for TEEG using only 9 features. Most errors of pylon are appeared near ground and vegetation because they include nearby ground and vegetation as their neighbourhoods while computing the features.

Class	Veget	Wire	Pylon	Bldg	Accuracy(%)
Veget	63,491	48	13	575	99.00
Wire	97	5,831	50	23	97.17
Pylon	103	106	856	2	80.23
Bldg	656	27	0	23,528	97.18

Table 4. Confusion matrix for TREG using 9 important features

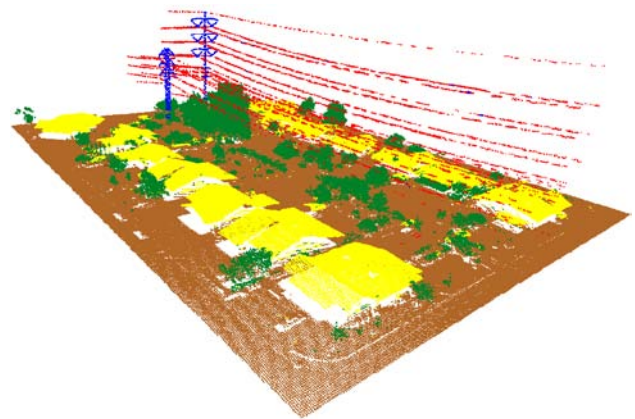


Figure 6. Classification map for TEEG using 9 features

5.5 Sensitivity analysis on segment size

The derived features from two applied volumetric approaches are very sensitive to the segment size. For determining the best segment size we perform a sensitivity analysis on it. The 9 features of the TREG are tested for comparing classification performance with respect to 2m to 7m segment sizes (Figure 7). As expected, too large and small segment sizes show worse classifications due to the multi-class points and scarce points in a segment. Therefore, 3m is chosen as the best segment size.

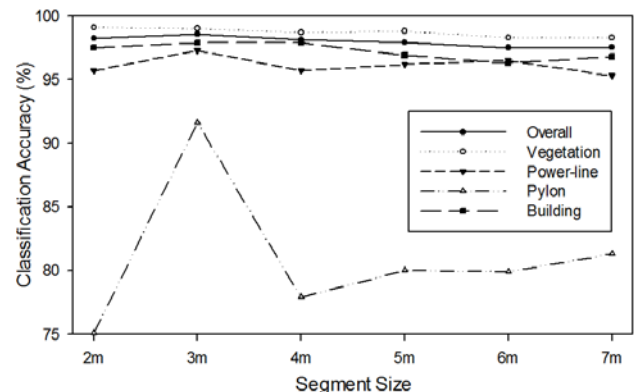


Figure 7. Comparison of classification performance on segment size (with TREG)

6. CONCLUSIONS

This research investigates 21 features which are able to respectively highlight five classes: ground, vegetation, power-line, pylon, and building, which can be typically found in a

power-line scene from LIDAR data. The *Hough Transformation (HT)* and *vertical profile* analysis are newly attempted for detecting power-line and pylon which are major electric utilities in the power transmission system. The considered features are computed through voxel- and sphere-based volumetric approach. The RF then is applied based on the derived features. From the comparative analysis of them, we conclude the voxel-based feature extraction makes an acceptable classification result, but the point-based approach (sphere-based feature extraction) is more uniform in terms of all the classes. In addition to feature extraction, the effect on the class frequency is tested to create an unbiased classifier of each class by making samples to have uniform distribution as removing ground, which is typically the most dominant class in sub-urban and power-line scene. As the result, vegetation, pylon, and building classification are a little improved but, there is no enhancement of power-line despite an increasing importance of *HT*. We try to select several important features which are relevant to structures in power-line scene without ground. The selected 9 important features are applied to the test sample (TE) in order to compare with the case of using all features. In the test classification performance of 95.9% success rate is achieved compared to 96.4% of all feature used method. Major misclassification is mainly appeared in pylon parts near ground and vegetation due to close proximity. The 3m of segment is chosen as the best size for feature extraction from a sensitivity analysis on it. For the validation of our approach, a comparison with other classification methods is necessarily required, but this study more focuses on the investigation of extractable features from LIDAR and the selection of important features closely related to power structures. Therefore, the comparison will be performed for future work.

ACKNOWLEDGEMENTS

This research has been sponsored by Ontario Centres of Excellence (OCE) and Geo Digital International (GDI) for the project named "Spatiotemporal Risk Management of Power-line Networks". Recently released Weka 3.6 is available on this site (<http://www.cs.waikato.ac.nz/ml/weka/>). In this study, Weka 3.5 customized by Livingston, F. was used, so we are much appreciated that he distributed it free. It can be downloaded from <http://www4.ncsu.edu/~fjliving>.

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