AUTOMATIC CLASSIFICATION OF URBAN OBJECTS FROM MOBILE LASER SCANNING DATA

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ABSTRACT:

The study deals with the automatic supervised classification of urban objects from point clouds collected by the vehicle-based Mobile Laser Scanning (MLS) system. A benchmark dataset representing the Technical University of Munich (TUM) City Campus was used. The main contribution of this article is evaluating the performance difference between kNN, cylindrical and spherical local neighborhood relations in point-based classification of an MLS system using local geometric and shape-based features. The Random Forest (RF) classifier was performed for 8 manually marked classes in the benchmark set: artificial terrain, natural terrain, high vegetation, low vegetation, building, hardscape, artifact and vehicle. We reveal that the cylindrical neighborhood with 13 attributes provides an improvement of 5.2% compared to the spherical neighborhood, while the kNN gave almost the same result as the cylindrical neighborhood (0.8% improvement) in the shortest time. Finally, a new feature set was created by combining the most important features obtained from different neighborhood types. As a result, we achieved 96.9% overall accuracy by using 19 significant features obtained from all neighborhood types for the TUM-MLS1 point cloud.

1. INTRODUCTION

In recent years, accurate 3D spatial information has been important for use in many areas, including 3D city modeling, road and street planning and maintenance, location-based services, virtual reality, vehicle navigation, and so on. Therefore, it is important to rapidly acquire high-accuracy 3D data. Due to its ability to generate dense and precise 3D point clouds, LiDAR technologies are one of the most favored approaches in mapping and surveying studies. Based on the platform they are installed on, they can be categorized as airborne, terrestrial, mobile, or spaceborne. Mobile systems are known to be one of the fastest, most accurate, and most thorough ways to collect data in cities.

Mobile Laser Scanner (MLS) systems are placed on a moving platform such as a car or a minivan, especially in street level surveys, and consist of 3D laser scanners, digital cameras, positioning and data storage units. All equipment is precisely calibrated to maintain minimal errors. Compared to other systems, urban acquisition with mobile laser scanning (MLS) is faster than with terrestrial laser scanning (TLS), and the resulting point clouds are much better quality and denser than aerial laser scanning (ALS) (Williams et al., 2013). Position information (X, Y, and Z) and color information are two attributes of point clouds obtained by laser scanning that contain surface information about objects. Hence, it does not carry information on which object on Earth's surface a particular point in the cloud belongs to. As a result, two questions arise: “Which points belong to a particular object?” and “What is the class of that object?”. No matter what approach is used to classify the point cloud, automatic classification relies on features derived from each individual point to assign a specific class to each of the points (or segments) within the cloud (Hemmes, 2018). In this context, a feature is any information about points in the dataset, and feature sets are basically created on the basis of four different types: geometric, radiometric, color, and contextual. The local properties of a point (or a segment) are defined as geometric features (e.g., shape, size, roughness, density). Density and color information can be recorded with MLS systems, and this information can be termed as radiometric and color features (Che et al., 2019). Finally, the spatial relationship between different points in a point cloud dataset is held by contextual features (Munoz et al., 2009). After attributes are extracted from the point cloud, a class label must be assigned to each point. For this purpose, machine learning methods (e.g., Weinmann et al., 2015; Xiao et al., 2016; Zheng et al., 2017; Sun et al., 2018; Thomas et al., 2018; Wang et al., 2018; Atik et al., 2021; Seyfeli and Ok, 2022a) or deep learning methods (e.g., Balado et al., 2019; Guo and Feng, 2020) can be utilized.

The goal of this paper is to perform a point-based supervised classification of point clouds collected using a vehicle-based MLS system in an urban area using the geometry and shape information of a point neighbor. During the evaluations, a benchmark dataset representing the Technical University of Munich (TUM) City Campus (Zhu et al., 2020) was employed. The dataset is composed of eight manually labelled classes: artificial terrain; natural terrain; high vegetation; low vegetation; building; hardscape; artifact; and vehicle. The local features for each point in the point cloud were computed via k-nearest neighborhood (kNN) (Weinmann et al., 2015; Seyfeli and Ok, 2022a), cylindrical (Demantké et al., 2012; Zheng et al., 2017; Seyfeli and Ok, 2022b) and spherical neighborhood (Thomas et al., 2018; Atik et al., 2021). All of these approaches have been studied thoroughly, and their classification performance has been evaluated. During the classification process, the widely utilized Random Forest classifier is employed. Finally, the classifier-based feature selection approach was used to determine the most important features obtained by all three methods.

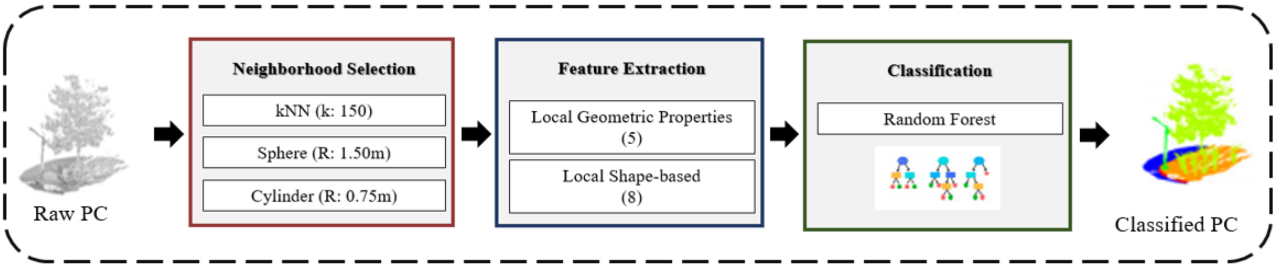

Figure 1. The overall workflow of the study.

The proposed framework (see Figure 1) was fully implemented on a desktop computer with an i7-9700K 3.60GHZ, 32GB RAM, using the MATLAB environment and CloudCompare, an open source 3D point cloud and network rendering project. The rest of this paper is structured as follows. Section 2 presents the applied methodology. Section 3 describes the dataset as well as the parameters that were employed. Section 4 presents the results and related discussion. Conclusions and future work are presented in Section 5.

2. METHODOLOGY

2.1 Neighborhood Selection

In point-based classification, each point in the point cloud is individually labeled. Geometric features of points in a close neighborhood are used to classify them, and the uniqueness of geometric features depends on the neighborhood. Therefore; identifying local neighbor points between points is one of the important steps in classifying MLS point clouds (Seyfeli, 2021). Different approaches can be used to collect local neighborhood information from the point cloud (Wang et al., 2018). The most commonly preferred definitions of "local neighborhood" are based on the spherical neighborhood, the cylindrical neighborhood, and the k-nearest neighborhood.

The K-nearest neighborhood is the type of neighborhood determined by the number of nearest points according to the Euclidean distance (Weinmann et al., 2017). Since the number of k points is fixed in this method, the area of interest is adjusted according to the point density and the closest points are selected. This means the kNN method does not have a fixed spatial neighborhood dimension. Spherical and cylindrical neighbors are created by defining a certain radius parameter. Compared to k-NN, the neighborhood size does not change even if the density changes since the radius is constant. For the study, the following fixed scale parameters for each neighborhood were used for the data set by evaluating the results of previous studies (Seyfeli, 2021) and the feasibility of data processing.

- $N_{kNN,\,150}$: k is 150 nearest points,
- $N_{S\,,\,1.5}$: the sphere has a radius of 1.5 m,
- $N_{C\,,\,0.75}$: the cylinder has a radius of 0.75 m.

The clarification of local neighborhood information (length, size, shape, etc.) is crucial to obtaining a satisfactory result since point density in MLS-based point clouds is variable for certain reasons (occlusion, changing scanning angle, and varying distance) (Demantké et al., 2012). In most cases, neighborhood definitions can be performed with a single scale parameter (radius or number of nearest points), and prior knowledge of the data can be very useful for appropriate selection of this parameter. There are also suggested approaches for selecting the most appropriate neighborhood size based on the data, which aim to support different neighborhood sizes for different classes. Instead of a single scale, multiple scales of the point cloud can be used to characterize the local 3D structure. This can be created by combining different neighborhood sizes or by different neighborhood types (e.g., spherical and cylindrical neighborhood combinations) (Weinmann et al., 2017). Point-based features are generally sensitive to point density, so multi-scale features can be useful to improve classification performance. Basically, the methodology is performed according to the following steps for all approaches:

1. Let X_i be any point in the MLS point cloud. Each X_i is taken as the center.
2. The scale value is determined. In this case, the scale value is the radius r for cylindrical and spherical neighborhoods, and the number of closest points k for kNN.
3. A 3D local neighborhood is spanned up around the point in the center based on a fixed scale.
4. Points in the neighborhood are determined. These points are used for the feature extraction step.

2.2 Feature Extraction

A classifier can be run by computing features from the immediate vicinity of each point in the point cloud and using the geometric features gathered from the spatial arrangement of these 3D points. If the respective mobile system also allows the capture of additional information that may be relevant to the classification task (e.g., intensity or color information in the form of RGB values), this information can be used to identify further properties. The extracted geometric features depend on the neighborhood type and the respective classifier. The features are usually derived by describing the geometric properties of the defined local neighborhood. The features comprise five 3D geometric properties of the considered local neighborhood, which are given by the normalized height of a point (H) of the considered 3D point X_i, the number of points in the neighborhood (N), verticality (V), and the height difference (ΔH) as well as the standard deviation of the height (σH) values corresponding to those 3D points within the local neighborhood (Seyfeli, 2021). The height of a point in the MLS point cloud is given based on a reference surface, i.e., the ellipsoidal surface (Z). In this study, normalization was performed to calculate the height from the ground of each point. For this purpose, the Cloud Simulation Filtering (CSF) plugin (Zhang et al., 2016) of the Cloud Comparison software is applied to extract the ground surface height.

Furthermore, many studies have referred to the use of local 3D shape features derived from the 3D structure tensor. These features rely on eigenvalues λ_i with i=1,2,3.

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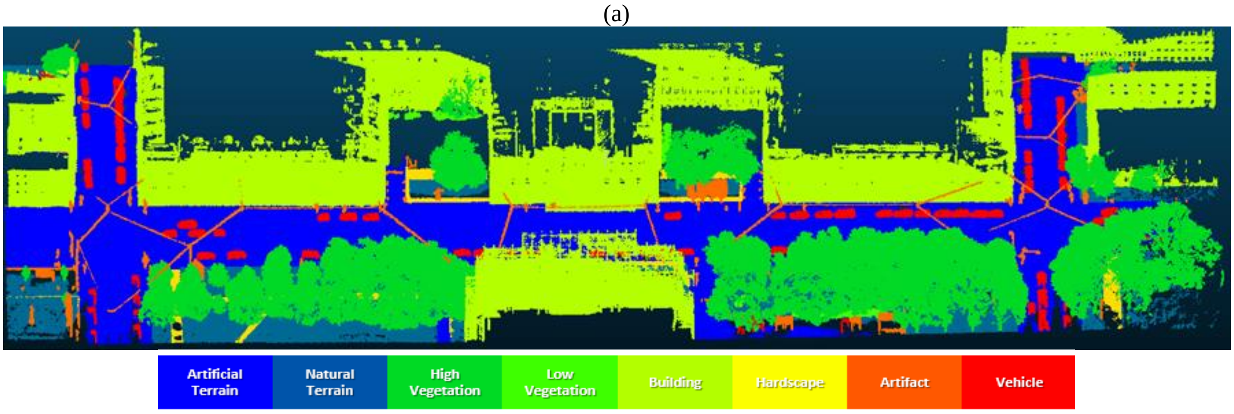
(a)



(b)

Figure 2. TUM-MLS1 (a) real scene representation, and (b) an eight-semantic labeled point cloud (Zhu et al., 2020).

Principal component analysis (PCA) provides key aspects of the point distribution in 3D and magnitudes of variation of the point distribution based on the neighborhood's centroid (Demantké et al., 2012). PCA is used to construct a covariance matrix for each point in the neighbors and evaluate the eigenvalues generated from the covariance matrix (Guan et al., 2016). The coordinates of neighboring points specify a shape with eigenvalues obtained from the 3×3 covariance matrix. The eigenvalues are positive and are ordered as $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$. The eigenvalues measure the goodness of the planar and linear fits. The neighborhood defines a 3D line shape when one of the eigenvalues is large and the others are close to zero. If two eigenvalues have nearly the same value and the other is close to zero, the neighborhood forms a 3D plane. Other than that, if they are all large, it creates a 3-dimensional spherical or fuzzy surface (Zheng et al., 2017). Eight 3D shape properties, also known as eigen-based properties, are represented by linearity (L_λ), planarity (P_λ), sphericity (S_λ), omnivariance (O_λ), anisotropy (A_λ), eigenentropy (E_λ), sum of eigenvalues ($\sum\lambda$), and change of local curvature (c_λ).

2.3 Classification

Within the scope of our work, derived features serve as inputs to distinguish classes in the data set. For such a classification task, a Random Forest (RF) classifier (Breiman, 2001) can be used to achieve a good balance between accuracy and efficiency. RF is a tree-structured classifier that consists of a classification (or regression) tree built on random data samples. This method is one of the most preferred machine learning methods for high-density MLS data.

3. DATASET AND EXPERIMENTS

The study area covers the city campus of the Technical University of Munich (TUM) (Figure 1), which is located in Munich, Germany (48.1493° N, 11.5685° E). The test dataset TUM-MLS1 was acquired by the vehicle-based MLS platform MODISSA on April 18th, 2016. The point clouds were collected using two Velodyne HDL-64E cameras set at a 35° angle on the vehicle's front top (Sun et al., 2018). The dataset requires 62 GB of storage, and each point within the dataset has 3D coordinates (X, Y, and Z) and an intensity value (thermal information). It represents the urbanized landscape, including high-rise building facades. The dataset includes the following classes: artificial terrain (1), natural terrain (2), high vegetation (3), low vegetation (4), building (5), hardscape (6), artifact (7), and vehicle (8), and there are 3,039,327 manually labeled points in the ground truth data (see Figure 2).

The data set was divided into test (about 75%), validation (about 5%) and training (about 20%) parts with the holdout technique, which is one of the cross-validation methods that randomly divides the data set, so that the classification model was estimated with the training data and the performance of the trained model was internally evaluated with the validation data. Finally, test data was used independently to evaluate classification findings (Seyfeli, 2021). The parameters necessary to initialize the methodology are presented in Table 1.

The importance of the features used during the classification and described in Section 2.2 was tested with the “Out of Bag Predictor Importance Estimates” of the RF algorithm of MATLAB, which is a classifier-based feature selection method. It has been found that the most important parameter for all neighborhood types is the normalized height (H) of a point. The strength of the association between predictor pairs can be inferred using predictive association elements. The tests revealed a high correlation between sphericity and anisotropy properties, with an almost 100% correlation for all neighborhood types. Also, the curvature was highly correlated with these two predictors for kNN and cylindrical neighborhood. Based on the out-of-bag importance and predictor association estimates, the following feature sets were selected:

- N_{kNN} : L_λ, P_λ, S_λ, O_λ, E_λ, V, H, ΔH, σH
- N_S : L_λ, O_λ, $\sum\lambda$, c_λ, H, N, ΔH
- N_C : H, N, ΔH

Section	Parameters	{Tested} / "Selected"
2.1	k value (N_{kNN})	150 points
	radius (N_S)	1.50 m
	radius (N_C)	0.75 m
2.2	# of features (N_{kNN})	{ 12, "9" }
	# of features (N_S)	{ 13, "7" }
	# of features (N_C)	{ 13, "3" }
2.3	# of trees	{5, 10, 15, 20, "25", 30}
	# of variables (n) to select for each decision split, √n	3
	minimum # of observations per tree leaf	1 (default)

Table 1. Parameter settings.

4. RESULTS AND DISCUSSION

4.1 Results for Different Neighborhood Definitions

To understand how local neighborhood information affects the classification result, three local neighborhood information methods (kNN, spherical, and vertical cylindrical neighborhood) were evaluated, and all numerical results are reported in Table 2. Based on the tests performed, the lowest classification accuracy was achieved when neighborhood relationships were established via local spherical neighborhood. The overall accuracy and kappa index, respectively, were computed to be 90.1% and 85.8%. Confusion between high vegetation and building classes, as well as artificial terrain and natural terrain classes, were the most common sources of classification errors. The producer's accuracies of three classes as low vegetation, hardscape, and artifact were found to be less desirable (≈ 51-61%) in this scenario. However, the local spherical strategy was more successful than the kNN method in extracting the hardscape class.

The overall accuracy of the test data was calculated to be 94.5% in the scenario of kNN local neighborhood. Despite the fact that this result is substantially better than the spherical neighborhood outcomes, a number of points corresponding to the classes of building and high vegetation were misclassified. The low vegetation and hardscape classes' classification results were still found to be the lowest two of all classes. However, it should be noted that the kNN approach is the most effective way for distinguishing low vegetation.

In comparison to the other two local neighborhood definitions, the vertical cylindrical neighborhood produced the best overall outcome (95.3%). Despite the confusion between these two classes, high vegetation and building, both gave highly successful results with over 97.8% accuracy. Even in this case, the producer's accuracy of the class hardscape could not reach a satisfactory level. There are some classes in the dataset that have a small sampling size relative to others (e.g. low vegetation, hardscape, and artifact), and their classification accuracies were relatively low. Considering this, the high overall accuracy is due to the high accuracy of the dominant classes (e.g., artificial terrain, high vegetation, and buildings) in the dataset. As a result of the methods tested, the kappa coefficient was found to be between 0.85-0.93 for all neighborhoods. This means a nice agreement (Landis and Koch, 1977) between the predictions and the ground truth.

Since the features were calculated using the points collected in the local neighborhood, the processing time increases as the number of points in the neighborhood increases. As indicated in Table 2, the cylindrical neighborhood gave the best results. However, this comes at the expense of a significant increase in processing time (approximately 6 hours), particularly due to the computation of the covariance matrix to compute the shape features. Although the kNN method gave the second-best results, its processing was completed within 8 minutes, thus providing the shortest processing time. It was found that the spherical neighborhood processing is almost two times slower than the kNN method.

	N_{kNN}		N_S		N_C	
Class	P.A	U.A	P.A	U.A	P.A	U.A
A.T (1)	94.5	90.7	93.6	89.4	94.6	90.6
N.T (2)	83.4	80.7	82.0	81.8	83.3	82.7
H.V (3)	98.7	96.7	95.9	90.1	98.8	98.1
L.V (4)	67.0	84.5	61.1	85.0	66.1	82.2
B (5)	95.6	97.3	88.3	92.8	97.5	97.8
H (6)	53.6	80.9	55.8	83.9	56.6	79.5
A (7)	75.0	89.8	51.3	86.2	77.0	88.7
V (8)	85.6	88.6	85.5	86.2	85.0	87.1
O.A.(%)	94.5		90.1		**95.3**	
Kappa	0.92		0.85		**0.93**	
Time (min)	7.44		14.60		355.08	

Table 2. Accuracy results of all neighborhood types (O.A.: Overall Accuracy, P.A: Producer's Accuracy, U.A: User's Accuracy).

4.2 Result after the Combination of Features from Different Neighborhood Information

Considering the results presented in Section 4.1, a nice balance between accuracy and processing speed was achieved by the kNN approach. Consequently, 9 important features of kNN were chosen as base features. The classification result of the test data was assessed by subjoining 7 features of the spherical neighborhood and only the 3 important geometric features (H, N and ΔH) through the cylindrical neighborhood to the important features deduced from the kNN neighborhood. Since the normalized height (H) property is the same for all neighborhoods, duplicate features were removed. To perform RF classification, a total of 19 features were used as inputs. The classified point cloud is illustrated in Figure 3.

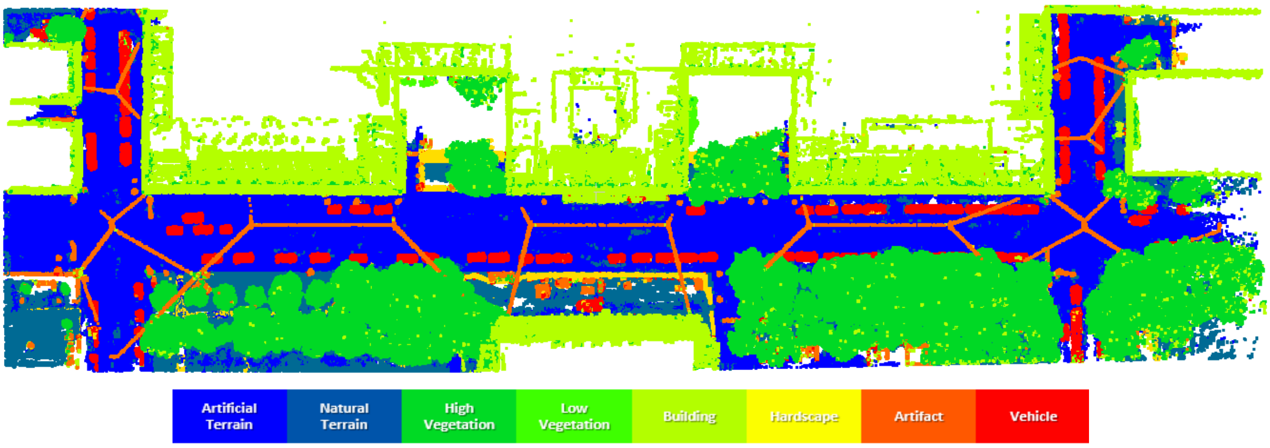


Figure 3. Classified outcome of the test dataset of TUM-MLS1 after combining features from all three local neighborhoods.

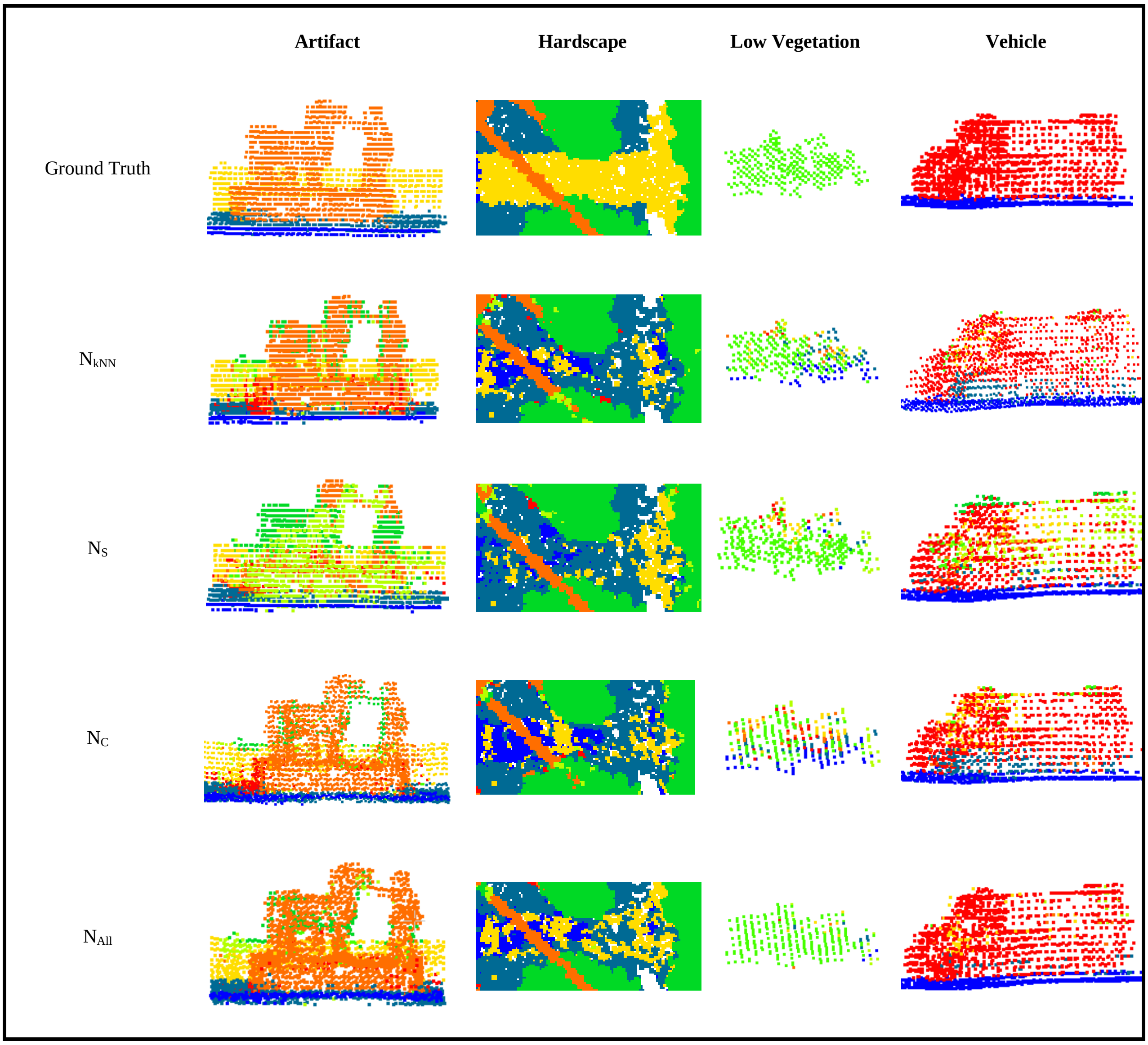


Figure 4. Classes of the TUM-MLS1 test dataset that were obtained with low accuracy (It belongs to the classification result of the different neighborhood type and their combination).

According to the results in Table 3, the overall accuracy increased to 96.9%. The artificial terrain, high vegetation, and building classes were obtained with an accuracy of over 95%. Besides, there is a great increase in the accuracy of classes such as low vegetation, hardscape, and artifact, which are found to be lower when individual neighborhood information is utilized (see Figure 4). Thus, a significant improvement has been achieved in the extraction of classes with small sample sizes by using 19 important features from all neighborhood types. The processing time, which was clearly a disadvantage of the cylindrical neighborhood, was now estimated to be roughly 67 minutes.

	N_{All}	
Class	P.A	U.A
A.T (1)	97.0	94.3
N.T (2)	90.2	91.0
H.V (3)	99.2	97.9
L.V (4)	84.9	95.3
B (5)	97.7	98.3
H (6)	72.4	93.1
A (7)	81.3	96.4
V (8)	93.9	93.5
O.A. (%)	96.9	
Kappa	0.95	
Time (min)	66.88	

Table 3. Accuracy result of combined features from all three neighborhood types (O.A.: Overall Accuracy, P.A: Producer's Accuracy, U.A: User's Accuracy).

5. CONCLUSION AND FUTURE WORK

The extraction of urban objects and automatic classification of vehicle-based MLS point clouds for an urban region are discussed, and all tests were performed on the TUM-MLS1 benchmark dataset. In terms of classification performance, three different local neighborhood relationships were examined over eight classes in the point cloud. Among the three neighborhoods, the best result was obtained with the cylindrical neighborhood, with 95.3%, and the worst result was obtained with the spherical neighborhood, with 90.1%. The kNN method is the fastest among them. Although the cylindrical neighborhood took the longest time to process, it produced the best results. By producing a feature set containing 19 features by using all three neighborhoods simultaneously, the extraction of these classes was particularly successful, and the overall accuracy was increased to 96.9%, the best result in all tests for TUM-MLS1.

For all neighborhood definitions, the kd-tree data structure was employed to effectively discover neighboring points. Other data structures, such as the octree schema, can be useful to improve processing speed. Since the processing load will increase as the data density increases, various approaches (segmentation, voxel, etc.) can be applied to alleviate the processing speed problem for better processing of large datasets.

Considering the geometric and shape features, it was observed that shape features are more important for kNN and spherical neighborhoods, while they have almost minimal effect on shape features when using cylindrical neighborhood. This may be due to the large variation in points in the cylindrical neighborhood. The normalized height was the most essential feature. Therefore, the method of obtaining the normalized height has a significant impact on the classification outcome. The accuracy of classes with a small sample size is also low, and there were some misclassifications in the classified point cloud. Depending on the point density of the cloud, the fixed scale selection may not be suitable for small sampled classes, so instead of using a single neighbor parameter for the entire data set, more than one parameter can be preferred for the size parameter.

In the future, we will go further into classification approaches for the MLS, such as deep learning. Other publicly available benchmark datasets will be used to test the proposed methodology. In addition, the feature set will be augmented with additional features, and the relevance of the features will be examined with the classifier-independent feature selection methods.

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REFERENCES

Atik, M.E., Duran, Z., Seker, D.Z., 2021. Machine Learning-Based Supervised Classification of Point Clouds Using Multiscale Geometric Features. IJGI 10(3), 187. https://doi.org/10.3390/ijgi10030187

Balado, Martínez-Sánchez, Arias, Novo, 2019. Road Environment Semantic Segmentation with Deep Learning from MLS Point Cloud Data. Sensors 19(16), 3466. https://doi.org/10.3390/s19163466

Breiman, L., 2001.Random Forests, Machine Learning, 45(1), 5–32, 2001.

Che, E., Jung, J., Olsen, M., 2019. Object Recognition, Segmentation, and Classification of Mobile Laser Scanning Point Clouds: A State of the Art Review. Sensors 19(4), 810. https://doi.org/10.3390/s19040810

Demantké, J., Mallet, C., David, N., Vallet, B., 2012. Dimensionality based scale selection in 3D LiDAR point clouds. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XXXVIII-5/W12, 97–102. https://doi.org/10.5194/isprsarchives-XXXVIII-5-W12-97-2011

Guan, H., Li, J., Cao, S., Yu, Y., 2016. Use of mobile LiDAR in road information inventory: a review. International Journal of Image and Data Fusion 7(3), 219–242. https://doi.org/10.1080/19479832.2016.1188860

Guo, Z., Feng, C.-C., 2020. Using multi-scale and hierarchical deep convolutional features for 3D semantic classification of TLS point clouds. International Journal of Geographical Information Science 34(4), 661–680. https://doi.org/10.1080/13658816.2018.1552790

Hemmes, T., 2018. Classification of Large Scale Outdoor Point Clouds Using Convolutional Neural Networks, MSc. thesis submitted to the Geomatics Faculty of Architecture & the Built Environment, Delft University of Technology, Delft, Holland.

Landis, J.R., Koch, G.G., 1977. The Measurement of Observer Agreement for Categorical Data. Biometrics 33(1), 159. https://doi.org/10.2307/2529310

Munoz, D., Bagnell, J.A., Vandapel, N., Hebert, M., 2009. Contextual classification with functional Max-Margin Markov Networks, in: 2009 IEEE Conference on Computer Vision and Pattern Recognition, IEEE, Miami, FL, 975–982. https://doi.org/10.1109/CVPR.2009.5206590

Seyfeli, S., 2021. Classification of Point Clouds Acquired Through Mobile Laser Scanner in Urban Areas Using Geometric and Shape Features, MSc. thesis submitted to the Dept. of Geomatics Engineering, Hacettepe University, Ankara, Turkey.

Seyfeli, S., Ok, A.O., 2022a. Classification of Mobile Laser Scanning Point Cloud in an Urban Environment Using kNN and Random Forest, in: Ben Ahmed, M., Boudhir, A.A., Karaș, İ.R., Jain, V., Mellouli, S. (Eds.), Innovations in Smart Cities, Springer International Publishing, Cham, 5, 963–973. https://doi.org/10.1007/978-3-030-94191-8_78

Seyfeli, S., Ok, A. O., 2022b, Classification of Mobile Laser Scanning Data with Geometric Features and Cylindrical Neighborhood. Baltic Journal of Modern Computing, 10(2), 209-223. https://doi.org/10.22364/bjmc.2022.10.2.08

Sun, Z., Xu, Y., Hoegner, L., Stilla, U., 2018. Classification of MLS Point Clouds in Urban Scenes Using Detrended Geometric Features from Supervoxel-Based Local Contexts. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. IV–2, 271–278. https://doi.org/10.5194/isprs-annals-IV-2-271-2018

Thomas, H., Goulette, F., Deschaud, J.-E., Marcotegui, B., LeGall, Y., 2018. Semantic Classification of 3D Point Clouds with Multiscale Spherical Neighborhoods, in: 2018 International Conference on 3D Vision (3DV). Presented at the 2018 International Conference on 3D Vision (3DV), IEEE, Verona, 390–398. https://doi.org/10.1109/3DV.2018.00052

Wang, Y., Chen, Q., Liu, L., Li, X., Sangaiah, A.K., Li, K., 2018. Systematic Comparison of Power Line Classification Methods from ALS and MLS Point Cloud Data. Remote Sensing 10(8), 1222. https://doi.org/10.3390/rs10081222

Weinmann, M., Jutzi, B., Hinz, S., Mallet, C., 2015. Semantic point cloud interpretation based on optimal neighborhoods, relevant features and efficient classifiers. ISPRS Journal of Photogrammetry and Remote Sensing 105, 286–304. https://doi.org/10.1016/j.isprsjprs.2015.01.016

Weinmann, M., Jutzi, B., Mallet, C., Weinmann, M., 2017. Geometric features and their relevance for 3D point cloud classification. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. IV-1/W1, 157–164. https://doi.org/10.5194/isprs-annals-IV-1-W1-157-2017

Williams, K., Olsen, M., Roe, G., Glennie, C., 2013. Synthesis of Transportation Applications of Mobile LIDAR. Remote Sensing 5(9), 4652–4692. https://doi.org/10.3390/rs5094652

Xiao, W., Vallet, B., Schindler, K., Paparoditis, N., 2016. Street-side vehicle detection, classification and change detection using mobile laser scanning data. ISPRS Journal of Photogrammetry and Remote Sensing 114, 166–178. https://doi.org/10.1016/j.isprsjprs.2016.02.007

Zhang, W., Qi, J., Wan, P., Wang, H., Xie, D., Wang, X., Yan, G., 2016. An Easy-to-Use Airborne LiDAR Data Filtering Method Based on Cloth Simulation. Remote Sensing 8(6), 501. https://doi.org/10.3390/rs8060501

Zheng, M., Lemmens, M., van Oosterom, P., 2017. Classification of mobile laser scanning point clouds from height features. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLII-2/W7, 321–325. https://doi.org/10.5194/isprs-archives-XLII-2-W7-321-2017

Zhu, J., Gehrung, J., Huang, R., Borgmann, B., Sun, Z., Hoegner, L., Hebel, M., Xu, Y., Stilla, U., 2020. TUM-MLS-2016: An Annotated Mobile LiDAR Dataset of the TUM City Campus for Semantic Point Cloud Interpretation in Urban Areas. Remote Sensing 12(11), 1875. https://doi.org/10.3390/rs12111875