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Automatic Non-Urban Road Surface Point Extraction Based on Geometric Features Using Neural Networks and Raster Structure Approach

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Abstract

The automatic segmentation of road surface points from 3D point cloud data has recently gained significant attention. However, it remains challenging due to the variability of road characteristics and the complexity of surrounding environments, especially in non-urban areas. This study introduces a comprehensive methodology leveraging neural networks to segment road surface points from non-urban point cloud data, supporting autonomous driving applications. The proposed approach computes multiple geometric features of the point cloud at two resolutions, 0.2 and 0.4 meters, to enhance segmentation accuracy. The features are projected onto a regular grid and converted into a raster format where each pixel's value represents the averaged features of points within its space. The rasterized values serve as structured inputs for a feature-based Neural Network (NN), which classifies road pixels based on intensity, density, curvature, planarity, roughness, surface variation, and verticality properties. Classified road pixels are further refined through morphological operations, distinguishing main road and road border pixels. The created masks are then used to extract the corresponding point cloud data of each category. The same neural network model is applied to extract road points within the border point clouds, where a precise road surface point cloud is obtained by merging the inside-road and filtered border points. The proposed method was evaluated on a MLS-acquired road point cloud dataset, achieving high performance with average completeness, correctness, quality, and overall accuracy rates of 98.9%, 97.6%, 96.6%, and 98.2%, respectively. Its key advantage lies in the reduced computational requirements demand by operating on rasterized inputs rather than traditional raw point cloud data.

1. Introduction

High-Definition (HD) maps play a crucial role in autonomous driving due to their highly precise and information-rich representations of road environments. As a result, HD mapping has gained significant attention in recent years (Bao et al., 2022). Creating HD maps requires detailed and accurate road surface data. Point clouds, which store comprehensive geometric and attribute details of scanned environments, serve as a key data source for both generating and updating HD maps (Chiang et al., 2022). Thus, effectively utilizing point cloud data is essential for producing high-resolution, reliable, and up-to-date maps that meet the demands of modern automated driving systems.

Manually segmenting road surface points from very big point cloud data is both labor-intensive and time-consuming. In addition, fully automated road extraction remains challenging due to the wide variability in road structures and the complexity of real-world environments (Y. Li et al., 2015; Martínez Sánchez et al., 2020; Xu et al., 2016). Unsupervised approaches often require manual feature extraction or preprocessing, which is difficult due to the irregular and unstructured characteristics of point cloud data. Moreover, the presence of noise, occlusions, and outliers further complicate the process (Chen et al., 2022). The variations in point cloud data based on the scanning device or technique introduce further challenges in developing robust algorithms capable of handling these differences while ensuring reliable road extraction.

To address these challenges, Artificial Neural Networks (ANNs) have become increasingly popular in point cloud semantic segmentation approaches (Zhang et al., 2019). ANNs are broadly categorized into Deep Neural Networks (DNNs) and Shallow Neural Networks (SNNs) based on the number of hidden layers and the presence of built-in feature extraction capabilities. DNNs typically consist of many hidden layers, sometimes up to hundreds, whereas SNNs have only a few layers (Gorokhovatskyi & Peredrii, 2018).

Recently, several DNN architectures have been developed for point cloud classification tasks. Some models provide point-by-point labeling, while others convert point cloud data into structured formats before classification such as multi-view representations (Su et al., 2015), voxel grids (Maturana & Scherer, 2015), or point grids (Le & Duan, 2018). DNNs have shown outstanding performance in classifying and segmenting 3D point cloud data (Diab et al., 2022). Their ability to capture complex patterns makes them highly effective for a variety of computer vision tasks. However, the deep architectures often necessitate large training datasets, which may not be practical in scenarios with limited annotated data (Lei et al., 2020). Additionally, the complexity of DNNs can make them difficult to interpret and fine-tune for specific applications.

SNNs offer an alternative approach, especially in structured environments like roads and achieving high-resolution road extraction results. Their simpler architecture enables faster training and inference while requiring fewer labeled samples (Fawzy, et al., 2023). While DNNs remain preferred for highly complex classification tasks, SNNs provide a lightweight and practical solutions for tasks where deep models may be unnecessary. Recent research has increasingly focused on the use of neural networks for point cloud segmentation, showing promising outcomes in urban environments where road markings and structures are well-defined. However, there is a gap in the literature regarding the applications of such techniques in non-

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urban areas, where roads tend to be less structured and more integrated with the natural landscape.

The current study presents a novel methodology for extracting road surface points in non-urban environments by leveraging point cloud geometric features and shallow neural networks. The approach computes multiple geometric features from the point cloud data, projects them onto a regular grid, and converts them into a raster format which reducing data complexity while preserving the accuracy. These structured raster values serve as inputs for a feature-based neural network to classify road pixels based on the geometric properties such as intensity, density, curvature, and roughness. Morphological operations refine the classification by distinguishing main road and border pixels, which are then used to extract the corresponding point cloud data. The same SNN model is applied to classify road points within border regions into road and non-road points. Consequently, a precise road surface point cloud is generated by merging the inside-road and filtered border points. The method enhances scalability, computational efficiency, and seamless geospatial integration by structuring data in a raster format instead of processing millions of individual points. Finally, the research aims to improve the accuracy and reliability of road surface segmentation which support the advancements in autonomous navigation and road infrastructure analysis.

2. Related Work

In recent years, researchers have made significant improvements in using ANN techniques for road point cloud extraction. (Rizzoli et al., 2022) reviewed the most common deep learning architectures for multimodal semantic segmentation in autonomous driving, in addition to the various techniques for combining multiple inputs such as color, depth, and other properties at different steps of the learning architectures, and their impact on performance. Point cloud classification methods using artificial neural networks are differ based on the input data type. Several researchers apply point-based approaches, where the point cloud data is processed directly, eliminating the need for data transformations such as voxelization or graph conversion, thereby improving computational efficiency. (Dowajy et al., 2025) applied a Shallow Neural Network (SNN) for fast and efficient road surface extraction using RGB values from photogrammetric point cloud data. Despite potential limitations from color similarities, minimal inputs, and the simple network architecture, the approach achieved high accuracy (completeness: 98.36%, correctness: 99.53%, quality: 97.90%, and overall accuracy: 99.87%). (Soilán et al., 2022) employed a deep-learning technique based on Point Transformer for the semantic segmentation of road point clouds acquired using Mobile Laser Scanning (MLS). The algorithm processes the point clouds directly, classifying the output like asphalt, road markings, road signs, and others. (Ma et al., 2022) automatically extracted road footprints from high-resolution co-registered images and airborne LiDAR point clouds in urban areas using the PointNet++ neural network. The network inputs were the raw LiDAR point features, such as 3D coordinates, intensity, etc., and the co-registered images' RGB Digital Number (DN) values. The extracted road points completeness and correctness were 84.7% and 79.7%, respectively. (Bai et al., 2021) employed the RandLA-Net point-wise neural net for automatic road-type classification of colored MLS point clouds. They investigated three input feature combination scenarios and their impact on classification results. The inputs included geometric features alone, geometric features combined with attribute features (e.g., color), and geometric features combined with local differences in attribute features. The findings showed that the second and third combinations had the highest overall accuracy of 86.23%. (Balado et al., 2019) proposed a method for MLS point cloud semantic segmentation of continuous elements in the road environment, including the road surface, ditches, fences, and borders. First, the point cloud is divided into sections along the road, and the PointNet neural network is applied directly to the points in those sections. The input features included point coordinates, intensity, return number, and total number of returns. The network training time was nearly 8 hours. The confusion matrix reveals that the overall segmentation accuracy for road surface points was 96.2%. (Dowajy et al., 2024) proposed a comprehensive approach using SNNs to segment non-urban MLS road point clouds for autonomous driving applications. The method converts raw point cloud data into a regular grid of cells or partial clouds. The SNN inputs were derived from the properties of partial clouds, including plane fitting error, average intensity, elevation range, and weighted density. The extracted road point clouds were further refined and assessed. The method's performance was evaluated, achieving completeness, correctness, quality, and overall accuracy close to 98%, 99%, 97%, and 98%, respectively.

Other researchers have investigated classifying road point cloud data using different data structures derived from the point cloud. (Caltagirone et al., 2017) presented a fully convolutional neural network for road extraction from MLS point clouds. An image was produced by projecting point clouds from the top view. Six statistics were calculated for each pixel in this image including the number of points, mean reflectivity, mean, standard deviation, and minimum and maximum elevation. Then, a pixel-wise semantic segmentation was implemented for road detection. The introduced system performance was compared with the best-performing algorithms on the KITTI road benchmark. (Fawzy, et al., 2024) designed, trained, validated, and implemented a CNN model in a built-up study area with building, road features. To enhance the classification capabilities, a MS image has been integrated with point cloud data which enabled deriving digital surface model, intensity, normal vector, surface variation, and vertical layers. The applied CNN model achieved an overall accuracy of 83.25% for the classification process and 87.00% for the post-classification refinement outperforming the traditional classification results. (H. T. Li et al., 2022) applied the mask Region-based Convolutional Neural Network (R-CNN algorithm) for road surface object segmentation in a 3D LiDAR point cloud captured by a Mobile Mapping Vehicle (MMV). The model inputs were a 2D image generated by projecting the point cloud intensity and height information. The result proved the model's efficacy in lane detection.

While the state-of-the-art approaches have achieved success, road point cloud classification has faced challenges associated with computational capacity, temporal constraints, and cost limitations. To overcome these challenges, the investigated work offers a new methodology that leverages point cloud geometric features and neural networks for extracting road surface points in non-urban environments.

3. Methodology

This paper proposes a structured methodology for extracting road surface points from non-urban point cloud data by employing point cloud geometric features and neural networks. (Figure 1) provides a clear, step-by-step flowchart outlining the research methodology and procedures.

4. Experimental Works

4.1 Study Area and Data Used

The performance of the proposed method was evaluated using a mobile mapping point cloud dataset collected from the 3 km long Handling Course at the ZalaZone automotive proving ground in Hungary (Figure 2). A Leica Pegasus: two mobile mapping system was used for data acquisition. It is built of a Z+F Lidar unit with a 120 m range and 360° field of view, along with seven cameras (2046 × 2049 pixel, 24-bit). The lenses have an 8.0 mm focal length, except for the zenith camera (2.7 mm). Images were captured at 8 fps. Positioning was ensured by a Novatel GNSS/IMU system. The dataset consists of 109 million colored road points.

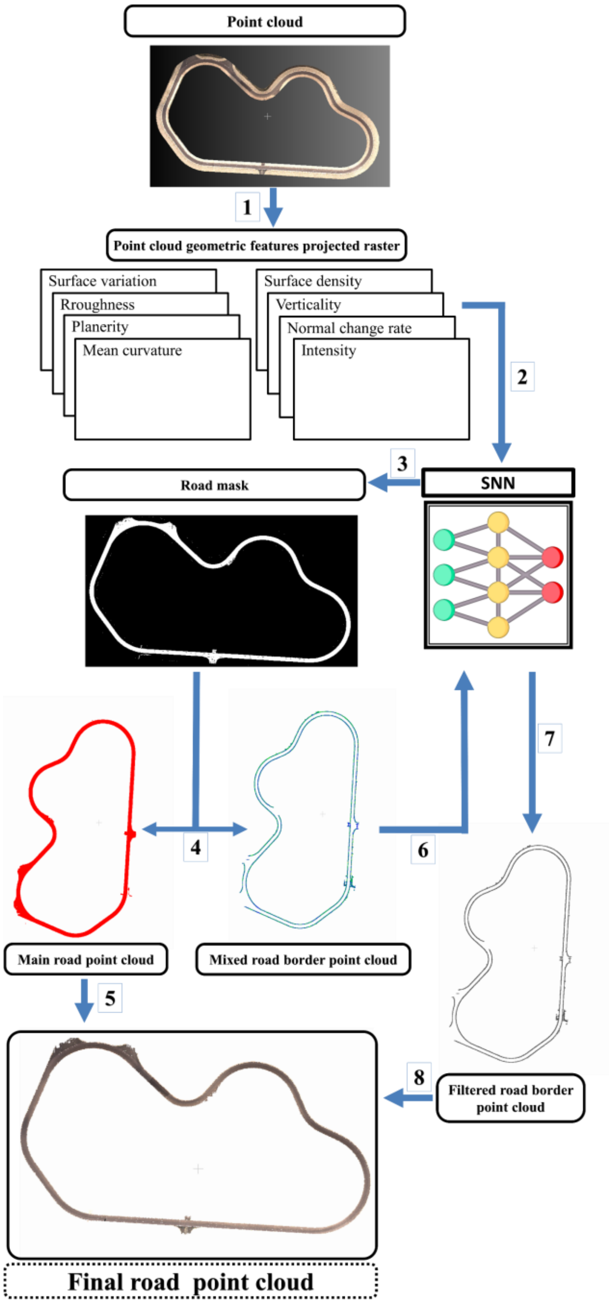

Figure 1. Procedures of the presented methodology.

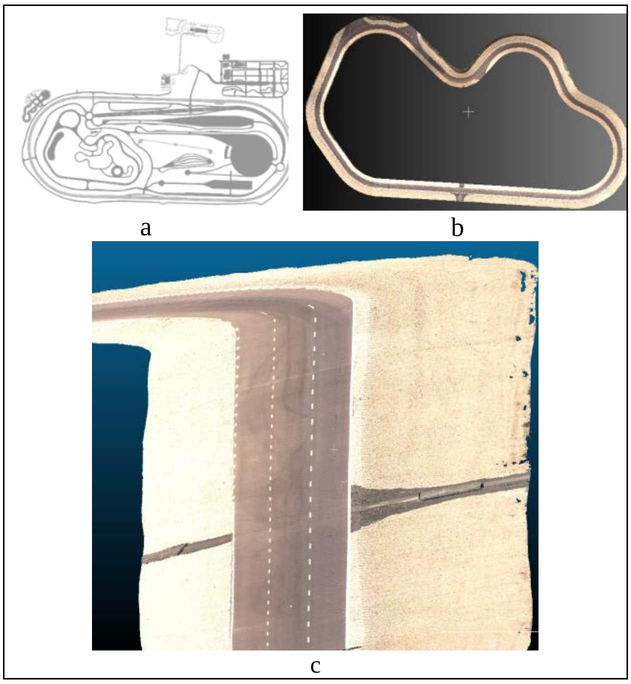

Figure 2. Study area: (a) ZalaZONE Proving Ground, (b) Study area point cloud (general view), and (c) Point cloud of the study area (detailed view).

4.2 Input Features

4.2.1 Intensity

Point intensity refers to the return strength of the laser pulse that generated the point. Intensity differs based on the reflection characteristics of the material surface, offering the distinguishment of different materials or objects. Intensity is crucial in point cloud classification and object detection, especially for road extraction, as the road surface points tend to have lower intensity values than other objects in the road environment. Consequently, the intensity index effectively highlights the distinctions between the road and non-road points within the road point cloud environment.

4.2.2 Geometric Features

Geometric features are tools that assess the point cloud-based statistics by extracting eigenvectors with attached eigenvalues from the data using the Principal Component Analysis (PCA). Eigenvectors and eigenvalues give an overview of the local shape of the point cloud when combined with other input parameters, such as the radius of the neighborhoods, density, and scale (Bazazian et al., 2015). In our study, several point geometric features were derived for each point within the point cloud by analyzing neighboring points within 20 cm and 40 cm radiuses. After experimenting with different searching radii, the optimal one was determined. The chosen radius demonstrates a significant variation between the road and non-road areas using the following extracted geometric features:

a) Verticality

The verticality represents the deviation of the local geometry of a point from the horizontal plane. It is calculated by measuring the angle between the normal vector of the point and the vertical axis. The normal vector is estimated based on the local geometry within the defined search radius (Hackel et al., 2016). This value distinguishes between the road and other objects whose surfaces exhibit vertical or slope geometry.

b) Surface Variation

The surface variation for each sample point with neighborhoods allows to determine whether the point belongs to a flat plane or a salient point (Edge) in the point cloud (Harshit et al., 2022). The road geometry tends to have flat surfaces, resulting in lower surface variation compared to neighboring objects.

c) Planarity

Planarity indicates how much the local point distribution resembles a planar surface. A high value suggests that the points are well aligned along a plane, while lower values indicate a more scattered distribution.

d) Normal Change Rate

Normal change rate presents the variation in surface normal between neighboring points in a 3D point cloud, indicating surface orientation and discontinuities changes.

e) Roughness

Roughness quantifies the deviation of a surface from a perfectly smooth plane. It is typically measured as the standard deviation of point distances from a locally fitted plane.

f) Mean Curvature

Mean curvature describes the local bending of a surface and is defined as the average of the principal curvatures at a given point.

g) Surface Density

Surface density refers to the number of points per unit area in a point cloud to reflects how dense a surface is.

4.2.3 Rasterization

After computing the point cloud geometric attributes, features are converted into raster format. The conversion involves projecting the point-wise features onto a regular grid. The pixel value in each resulting raster grid is calculated by averaging the features of all points that fall within the corresponding pixel. The geometric resolution of the output raster was set to match a 0.5 × 0.5 m resolution, which is suitable for road scan density and typical road dimensions.

4.3 Shallow Neural Networks

The study utilizes a feature-based shallow neural network with one hidden layer consisting of ten neurons (Figure 3). The network uses point cloud intensity and geometric features as inputs to predict the corresponding class. The model was trained using feature values extracted from raster pixels to categorize them into road and non-road classes. After training, the network was applied to classify the raster image into road and non-road pixels, thereby segmenting the road surface. Additionally, the same neural network architecture can process features directly extracted from the point cloud and classify individual points as road or non-road. The model flexibility allows the network to work with both raster and point cloud data formats.

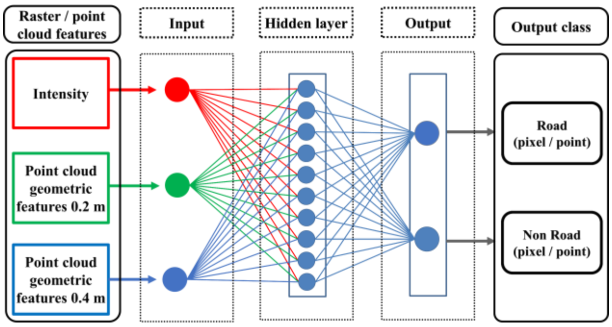

Figure 3. SNN network data processing architecture.

5. Results and Discussions

The trained cell-based SNN model was utilized to generate a binary road mask (Figure 4). However, in certain instances, bad road conditions or surface damage could lead to the misclassification of specific regions of the road as non-road pixels. To solve this issue, a dilation morphological operation was applied to identify and restore any missing areas within the detected road surface. Next, additional morphological operations were employed to classify the road mask into road and road border pixels. The resulting masks were then used to integrated with the point cloud and segment the corresponding road points. Since the road border point cloud was generated using a raster mask, resolution limitations led to including both road and non-road points. To enhance segmentation accuracy, a feature-based SNN model was employed to refine the extracted border data. The network effectively filtered out non-road points by utilizing points' geometric features, achieving a more precise road structure (Figure 5). The road surface point cloud is then generated by combining the main road point clouds with the refined border point cloud.

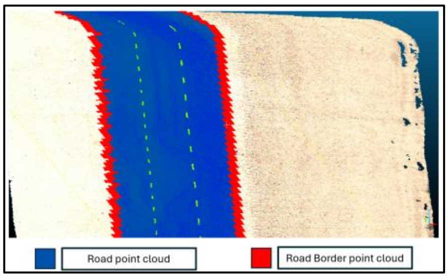

Figure 4. Road and road border point clouds.

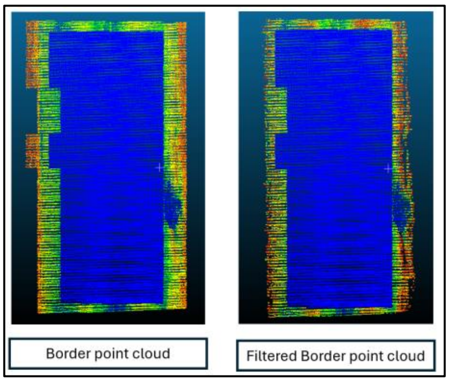

Figure 5. Border point cloud filtering using feature-based SNN.

5.1 Accuracy Assessment

Four quality metrics, completeness, correctness, quality, and overall accuracy (Equations 1-4), proposed by (Heipke et al.,

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1997) were used to quantitatively assess the method’s effectiveness in extracting road points. The assessment involved comparing the classification results with a manually labeled ground truth point cloud.

$$\text{Completeness} = TP/(TP+FN) \tag{1}$$

$$\text{Correctness} = TP/(TP+FP) \tag{2}$$

$$\text{Quality} = TP/(TP+FP+FN) \tag{3}$$

$$\text{Overall accuracy} = (TP+TN)/(TP+FP+FN+TN) \tag{4}$$

Where TP (True Positive) represents the count of correctly classified road points, FN (False Negative) is the number of road points misclassified as non-road, FP (False Positive) is the number of non-road points that are misclassified as road points, and TN (True Negative) refers to the number of non-road points that are classified correctly. The values were calculated using Equations 5-8.

$$TP = road\ points_{truth} \cap road\ points_{classified} \tag{5}$$

$$TN = non\_road\ points_{truth} \cap non\ road\ points_{classified} \tag{6}$$

$$FP = non\_road\ points_{truth} \cap road\ points_{classified} \tag{7}$$

$$FN = road\ points_{truth} \cap non\ road\ points_{classified} \tag{8}$$

The detailed confusion matrix of the proposed method is presented in Table 1. The comparison of the classification results to the validation data demonstrated the efficacy of the proposed method in road point cloud extraction. The overall classification accuracy (98.15%) refers to the percentage of points in the dataset that were correctly classified, considering both road and non-road classes. The completeness (98.91%) is the percentage of correctly classified road points compared to the total number of road points in the ground truth data. The correctness (97.59%) indicates the points classified as ‘road’ were indeed road points. The quality score (96.56%) represents the percentage of the road points in the dataset that were correctly classified, considering both true positives and negatives.

		True label		
	Classified data	***Road***	***Non- Road***	**Total points**
Predicted label	***Road***	62,012,372	1,530,373	63,542,745
	Non- Road	681,376	55,217,654	55,899,030
Total points		7,282,938	62,693,748	56,748,027
TP		62,012,372	Completeness	98.91%
TN		55,217,654	Correctness	97.59%
FP		1,530,373	Quality	96.56%
FN		681,376	Overall accuracy	98.15%

Table 1. The results of the proposed method.

The proposed method demonstrates strong classification capabilities, particularly in distinguishing road and non-road features. The key advantage is the rasterization approach, which simplifies data processing while maintaining accuracy. The method’s efficiency is further enhanced by its lightweight neural network, minimal training data requirements, and direct applicability to raster and point-wise LIDAR data. Integrating geometric features has proven effective in differentiating road and non-road areas, even on smooth or visually similar surfaces; however, certain limitations should be considered. The simple architecture of the SNN model constrains its ability to learn complex patterns, and its reliance on geometric features necessitates high-quality road scans for optimal accuracy.

6. Conclusions and Future Works

The study introduces a novel non-urban road surface extraction approach from point cloud data, leveraging geometric features, rasterization, and neural networks. The proposed method achieves high accuracy and computational efficiency, making it well-suited for autonomous driving applications in non-urban settings. Future research will focus on refining the methodology, optimizing the neural network structure, and integrating additional inputs, such as color values, to enhance classification accuracy and adaptability across diverse environments.

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